Knowledge in the Dark: Scientific Challenges and Ways Forward

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Abstract
We propose the concept of *knowledge in the dark* – or short: *dark knowledge* – and outline how it can help clarify why in our current era of Big Data, the knowledge (i.e. evidence-based understanding) of people does not seem to be substantially increasing despite a rapid increase in produced data and information. Key reasons underlying dark knowledge are: (1) the production of biased, erroneous or fabricated data and information and (2) the inaccessibility of data and information, both for example due to sociopolitical or financial interests; (3) the incomprehensibility of data and information, for instance due to specialized jargon and complex disciplinary knowledge; and (4) the loss of previous knowledge due to, for example, the extinction of scientific disciplines. OECD data show that only a fraction of the global investments into research and development are done with the principal intention to increase public knowledge. Most investments are by the industry, steadily increasing with time, whereas governmental investments have been decreasing in relative GDP terms. This pattern suggests an increasing privatization of knowledge. But also in the academic realm, where increasing public knowledge is a primary aim, several factors lead to dark knowledge. We highlight four of these factors – loss of academic freedom, research biases, lack of reproducibility and the Scientific tower of Babel – and offer ways forward to tackle them, for example establishing an international court of arbitration for research and developing advanced tools for research synthesis.

Key words: agnotology, knowledge-ignorance paradox, Matthew effect, open science, reproducibility, research biases, Scientific tower of Babel

Introduction

Today, the quote by John Naisbitt that "we are drowning in information but starved for knowledge" (p. 24 in Naisbitt 1982) is more applicable than ever before. Thanks to smartphones and similar devices, we have instant access to enormous amounts of data and information. At the same time, we seem to lack in capacity to transform available information into knowledge related to important decisions for our daily lives, such as health care or economic investments (Ungar 2008). Evidence suggests that the general knowledge of individuals has not increased in the way that overall information and data have increased, a phenomenon termed knowledge-ignorance paradox (Putnam 2000, Ungar 2008, IEA 2010, Schulz 2012, Millgram 2015). Proctor (2016) even called the current age the "age of ignorance". Similarly, today's societies are increasingly seen as "post-truth societies" in which truth has partly lost its value and importance to people (Higgins 2016, Viner 2016).

Different perspectives and definitions exist about "knowledge" and related terms such as "reality" (Boghossian 2007, Moon and Blackman 2014, Nagel 2014). Assuming that an objective reality exists, we define knowledge as evidence-based understanding. It requires the reflection and interpretation of data and information. With "public knowledge", we refer to average evidence-based understanding by non-specialists (who have no privileged access to data and information).

How can we solve the conundrum that we are living in a time where data and information, and thus potential knowledge, keep accumulating, but where the actual knowledge of people does not keep up? The gap between actual (i.e. realized) and potential public knowledge can be seen as a lost opportunity – we term it *knowledge in the dark* or short: *dark knowledge* (Fig. 1). This term has not yet been applied in the emerging social science discipline called "agnotology" (Proctor and Schiebinger 2008); only "ignorance" has been widely used, however with different meanings (see Gross 2007 for standard terms used in this field). It seems useful to discriminate the different dimensions of public ignorance (i.e. the lack of public knowledge). Dark knowledge includes those dimensions of public ignorance where ignorance can in principle be reduced. It does not include ignorance that cannot be reduced: we humans cannot know everything. In Pinker's (1997, p. 561) words: "We are organisms, not angels, and our minds are organs, not pipelines to truth. Our minds evolved by natural selection to solve problems that were life-and-death matters to our ancestors, not … to answer any question we are capable of asking". Similarly, we humans do not want to know everything (e.g. Gigerenzer and Garcia-Retamero 2017), and we here focus on desirable knowledge.

Our use of the term "dark" was inspired by the terms "dark matter" in physics and "dark diversity" in biodiversity research. The former is probably well-known to most readers, and the latter describes the gap between potential and actual biodiversity in a given region (Pärtel et al. 2011).

There are at least four key reasons underlying dark knowledge (Fig. 1, right side). We have ordered them along consecutive steps in the process of knowledge production: how data and information are (1) produced, or not; (2) made publicly available, or not; (3) taken up by the public, or not; (4) and remembered by the public, or forgotten.

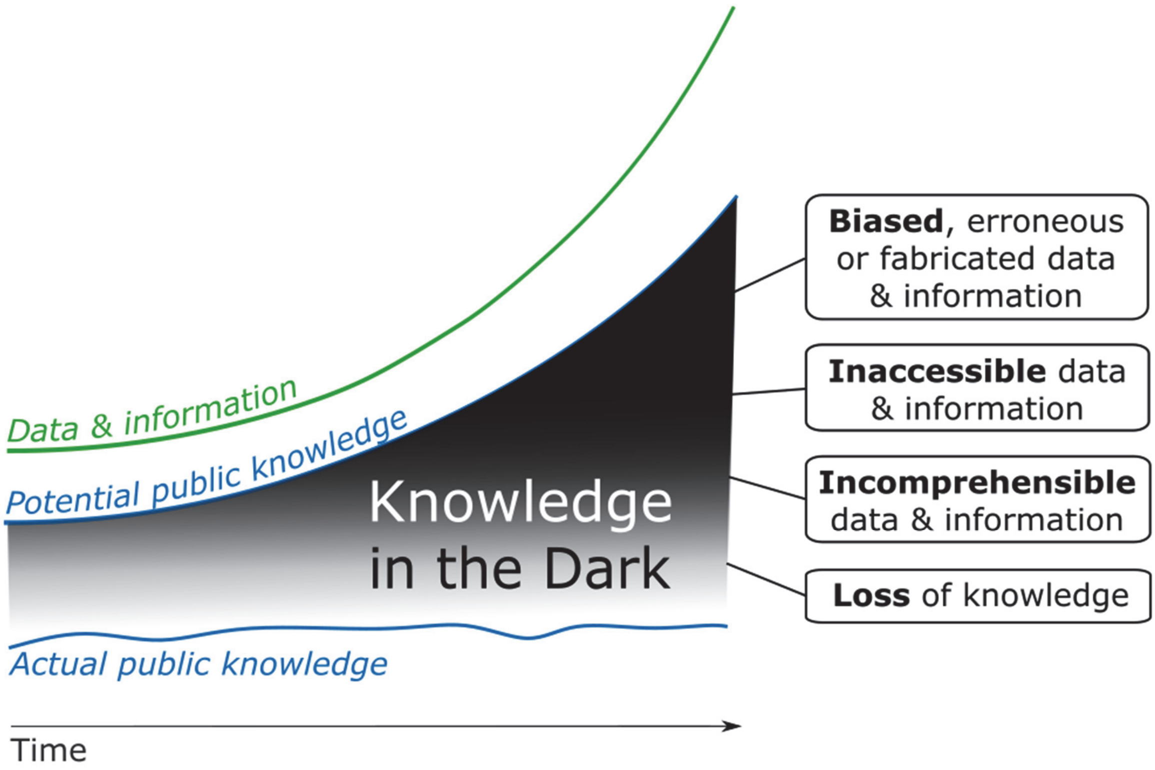

Fig. 1. *What is* knowledge in the dark *(on the left) and where does it come from (on the right)?* ***Left side:*** *knowledge in the dark is the gap between actual (i.e. realized) and potential public knowledge. The latter is rising due to increasing amounts of data and information. The exact size of the gap between actual and potential public knowledge is currently unknown, and so are the exact shape and position of the lines drawn. The graph thus lacks a y-axis and cannot be quantitatively read. Instead, the relative positions of the lines to each other are important. The curve for potential public knowledge is below the one for data & information, because it is not possible to translate all data and information into knowledge (e.g. Ackoff 1989).* ***Right side:*** *key reasons for knowledge in the dark.*

First, dark knowledge can be caused by biased, erroneous or fabricated data and information. For instance, the type of data and information produced can be influenced by financial or sociopolitical interests (Kitcher 2011). This can be combined with systematic disinformation, for example by the tobacco industry which successfully distorted the public understanding of tobacco health effects (Oreskes and Conway 2010). Similar strategies have been applied in the context of climate change (Oreskes and Conway 2010), by the sugar industry (Kearns et al. 2015) or pharmaceutical companies that hide information about their products from the public (Kreiß 2015, Crouch 2016). Finally, false information can now be actively spread with so-called bots, i.e. software applications running automated tasks (Howard and Kollanyi 2016, Kollanyi et al. 2016).

The second reason for dark knowledge is inaccessibility to existing data and information. For example, findings of secret services, the military and industry are typically inaccessible to the public (Resnik 2006, Proctor and Schiebinger 2008). Indeed, most people may not even be aware of the information and knowledge that have accumulated "in the dark".

The third reason for dark knowledge is that much information is incomprehensible for the public: although this information is accessible in principle, it can only be understood by experts, whereas other people find it incomprehensible, for instance because they do not understand the logic underlying these data and information, or the technical language in which these are outlined (see below for references and details).

The fourth reason is that previous knowledge has been lost. This is, for instance, the case if scientific disciplines disappear.

Why should scientists care about dark knowledge? Science is pivotal to advancing knowledge, innovation and evidence-based decision-making. It plays an essential role as a counselor (Pielke 2007). At the same time, there is a big risk that science is losing trust and thus its essential role in societies across the globe (Kitcher 2011). Indeed, we presently observe an increasing gap between scientific evidence and societal judgment (Funk and Rainie 2015), partly due to economic and ideological reasons.

Identifying solutions for tackling dark knowledge may contribute to defending serious, reflective and traceable reasoning within science and beyond. This article aims to take a step into this direction by (1) assessing the relative proportion of research investments done with the principal intention to increase public knowledge; (2) outlining underlying reasons of dark knowledge; and (3) suggesting ways forward. For the two latter goals, we focus on academic research as it is our core area of expertise. Yet dark knowledge is a general societal phenomenon and challenge, and the insights we offer may therefore be transferable to other professions and realms.

The world's top research investors

We are currently unable to quantify the total amount of dark knowledge (i.e. Fig. 1 is not scaled). However, data on the relative proportion of research investments by the industry, the military and secret services allow to roughly estimate the proportion of research *not* done with the principal intention to increase public knowledge. Looking at OECD countries (for which more comprehensive and comparable data are available than for other countries), this proportion is roughly three quarters, whereas governmental expenditures for civil research is only about a quarter (Fig. 2, OECD 2017). For the latter, we can assume that the principle funding intention indeed is to foster public knowledge, however public institutes may also have sociopolitical tasks or financial interests that lead to dark knowledge (see below).

Our results demonstrate that global expenditures into research and development (R&D) by the industry have been increasing through time, whereas governmental expenditures are – in relative GDP terms – lower today than they were in the 1980s (Fig. 2). In 2015, Volkswagen had the highest R&D budget of all companies worldwide, which was higher than the UK's governmental expenditures for civil research (Fig. 3). Samsung also trumped UK's budget, and Intel and Microsoft trumped Italy's budget.

Of course, not all research results from the industry, military or secret services remain hidden from the public and the borders are not always clear-cut. This is, for example, illustrated by the American Department of Defense Congressionally Directed Medical Research Programs (CDMRP, http://cdmrp.army.mil) which originated in 1992 with a focus on breast cancer research and now includes other medical research areas that are not of primary military interest but benefit the general public (Young-McCaughan et al. 2002). Nonetheless, a large fraction of the research results from the industry, military or secret services does remain hidden from the public. Companies intend to become economic leaders in their specific domain, and military supports geopolitical power and protect national interests (see also Resnik 2006). Thus, the results that do get public are often biased or selected, for instance to boost sales (e.g. for pharmaceutical products), to avoid legal restrictions (e.g. for tobacco or sugar) (Oreskes and Conway 2010, Kearns et al. 2015, Kreiß 2015, Crouch 2016) or to shape geopolitical decisions (Hartnett and Stengrim 2004).

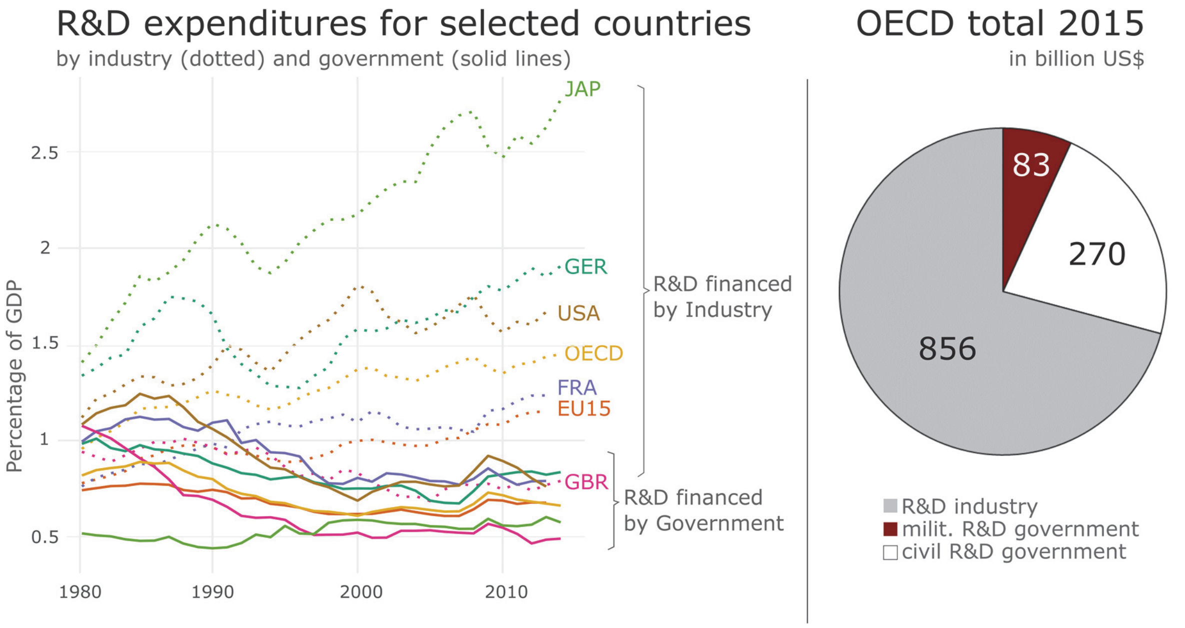

Fig. 2. *Global expenditures into research & development in several countries or groups of countries.* ***Left side:*** *temporal development of relative (as percentage of GDP) industrial and governmental expenditures.* ***Right side:*** *absolute (in billion US$) governmental expenditures of the OECD countries in 2015 divided into military and civil shares (the latter incl. universities) and compared to industrial expenditures (data from OECD 2017).*

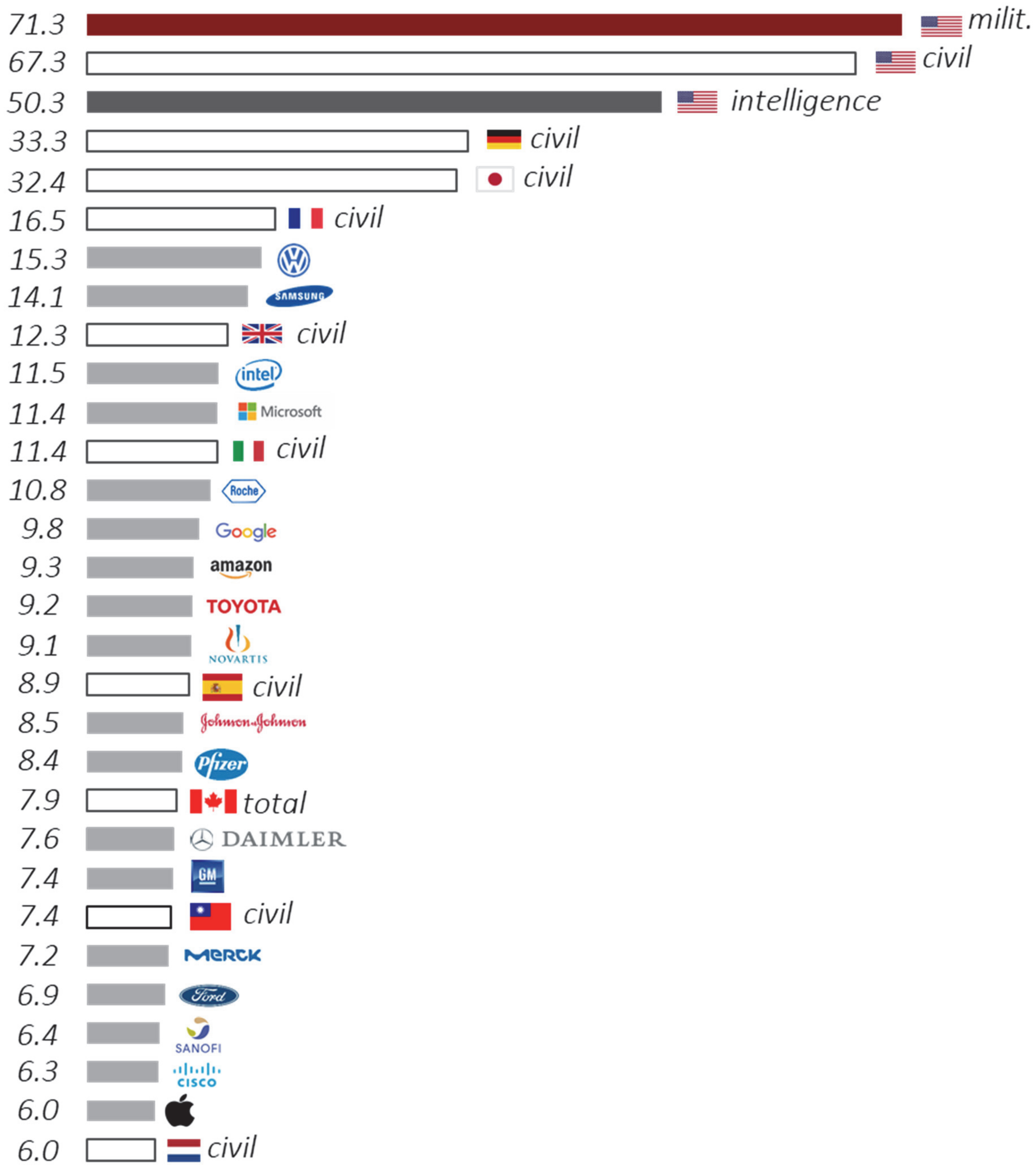

Fig. 3. *Selection of global top investors into research, development or intelligence in 2015: countries and companies with R&D or intelligence expenditures of 6 billion US$ or more in 2015 where data were available to us. Expenditures of countries are divided into military, intelligence and civil (incl. universities) due to the different interests and publication strategies of these sectors (data from: ODNI 2017, OECD 2017, PWC 2017; expenditures from countries such as China or India were not available to us).*

Knowledge in the dark in academia

Academic institutions do aim to increase public knowledge, yet they also produce dark knowledge. In this section, we emphasize four reasons underlying dark knowledge in academia: loss of academic freedom, research biases, lack of reproducibility and the Scientific tower of Babel (Fig. 4).

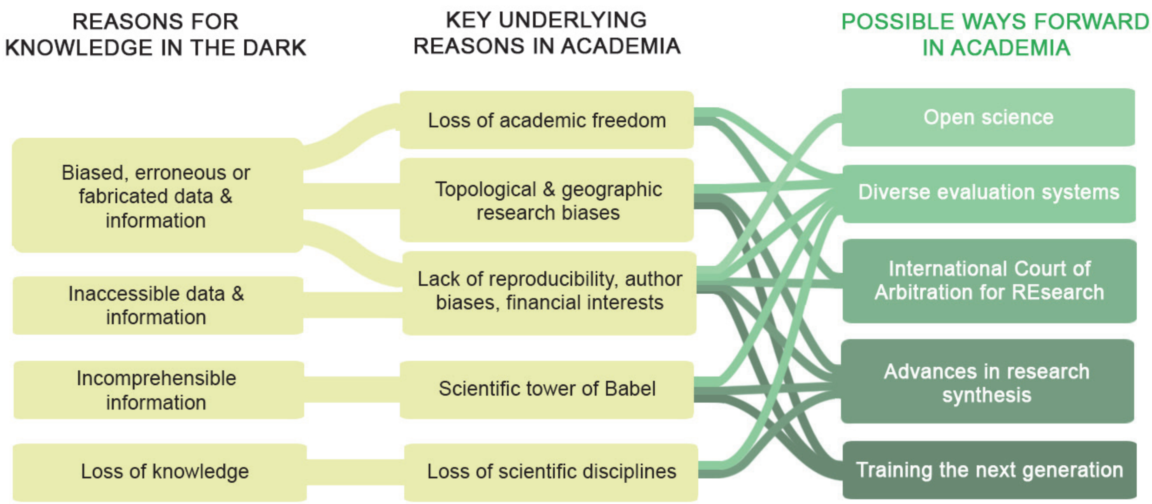

Fig. 4. *Key underlying reasons for knowledge in the dark in academia and possible ways forward. The general dimensions of knowledge in the dark (left section, from Fig. 1) are related to key challenges in academia (middle section; linkages are indicated by connecting lines). Possible ways forward to tackle each of these challenges are listed in the right section. Please note that the challenge "Loss of scientific disciplines" is not discussed in detail in the text.*

Loss of academic freedom

Academic freedom is pivotal for the functioning of democratic societies because independent and evidence-based knowledge is necessary to cope with the grand challenges societies are facing. In reality, however, individual researchers and institutions are not always free in what they investigate and teach, not even in democratic societies. Dramatic examples are being collected by the Scholars at Risk Network at http://monitoring.academicfreedom.info where cases are collected in which researchers lost their position, were prosecuted or imprisoned for political or other reasons.

A more subtle reason for a lack of academic freedom is the overuse of quantitative performance indicators such as the *h*-index, number of publications (in high-impact journals) or amount of grant money obtained. Such metrics have become increasingly popular in evaluating researchers and research institutions (e.g. Weingart 2005, Lawrence 2007, Fischer et al. 2012, Kaushal and Jeschke 2013, Arlinghaus 2014, Hicks et al. 2015, Jeschke et al. 2016). As a result, researchers focus on topics for which funding is available and that can likely be published in high-impact journals. This is particularly true if base funding is lacking or if researchers do not have a permanent position. Even in a wealthy country such as Germany, the relative proportion of permanent staff in science and arts at universities was only 17% in 2014 (Buschle and Hähnel 2016).

Moreover, third-party funding is partly steered through politically or economically motivated funding calls, frequently influenced by lobbyists (Kreiß 2015). In addition, private enterprises may exert influence on public research institutions through sponsoring professorships and infrastructure (Kreiß 2015, Crouch 2016), thus further limiting academic independence and freedom.

Academic research biases

The Matthew effect (Merton 1968) describes the phenomenon that established scientists receive disproportionate credit while lesser known scientists get little credit for their contribution. This "the rich get richer" phenomenon has been corroborated by analyses of scientific collaboration and citation networks (Perc 2014). It favors mainstream research while other topics are being ignored, particularly in a competitive environment with few permanent positions. Countless examples for topical research biases can be found across disciplines. For instance, economic research is still largely focused on neoclassical economy, whereas approaches such as ecological economics have remained underexplored (Van den Berg 2014). Another example comes from research on global environmental change where research has primarily focused on climate change, yet other critical topics such as environmental effects of synthetic chemicals have been poorly studied (Bernhardt et al. 2017).

Similarly, strong geographic biases can be found across research disciplines, since most research is typically concentrated in affluent countries, particularly in North America and Europe. This has direct and severe consequences for human health in other countries, as research on diseases limited to these regions is critically neglected (Kitcher 2011). Biodiversity research also has strong geographic biases towards North America and Europe even though biodiversity hotspots are primarily located in the Global South (Bellard and Jeschke 2016, Wilson et al. 2016).

Lack of reproducibility, author biases, financial interests

The first report of the Open Science Collaboration, which has performed extensive replicates of earlier studies in psychology, reported an average reproducibility of only 39% for 97 experiments (Open Science Collaboration 2015; see also Prinz et al. 2011, Ioannidis 2012). A similar phenomenon – which has been reported in psychology, too, but also in other disciplines such as medicine and biology – is that the strength of evidence, e.g. on the efficacy of a given drug or the empirical support for a scientific hypothesis, frequently declines over time ("decline effect"; Lehrer 2010, Schooler 2011, Jeschke et al. 2012).

Low reproducibility and decline effects can have several underlying reasons. Brian Nosek provides an example: "we interpret observations to fit a particular idea; we have already made the decision about what to do or think and our explanation of our reasoning is really a justification for doing what we wanted to do – or to believe – anyway" (quoted from Ball 2015). Such motivated reasoning is interlinked with fashions in science. For instance, scientists love new hypotheses, as they promise to move a given research field forward. Scientists thus typically want to find supporting evidence for a new hypothesis, particularly if it was proposed by themselves. Furthermore, studies supporting a new hypothesis are also easier to publish than those supporting established hypotheses. For the latter, it is however interesting to publish contradictory evidence. Such author biases can thus lead to a decline in empirical support for a given hypothesis over time (Jeschke et al. 2012).

Financial interests may also reduce reproducibility, cause decline effects and prevent access to data and information. For example, there is evidence that the pharmaceutical, tobacco and sugar industries strategically manipulated data and information about their products, particularly if they are brand new and need to be sold on the market in order to balance development costs (Lexchin et al. 2003, Oreskes and Conway 2010, Lexchin 2012, Kearns et al. 2015, Kreiß 2015, Crouch 2016).

The Scientific tower of Babel

Members of scientific disciplines use particular technical terminology, called "jargon", which is hardly understandable for non-specialists. Some technical terms are clearly identifiable as jargon, especially if they do not exist outside of the discipline. Other technical terms cannot be readily identified, as the same terms exist in everyday language, yet with another meaning, leading to misunderstandings. For example, we are using the term "ignorance" here as in everyday language, meaning "the lack of knowledge" (e.g. http://wordnet.princeton.edu); however, when social scientists use the technical term "ignorance", they frequently mean "knowledge about the limits of knowledge" (p. 751 in Gross 2007).

Technical terms are often helpful to accurately and succinctly write a scientific paper. This is particularly true if the target readership is within the boundaries of the same discipline. On the other hand, jargon hampers inter- and transdisciplinary work. Analyzing 709,577 abstracts published between 1881 and 2015 from 123 scientific journals, Plavén-Sigray et al. (2017) showed that the use of jargon in scientific texts has increased with time, and concurrently the readability of scientific texts has decreased. A total of 22% of scientific abstracts published in 2015 cannot even be considered readable by graduates from English-language colleges.

The rise of technical terminology is one key reason for the knowledge-ignorance paradox outlined above. Today, people have a high level of specialized knowledge but a relatively low level of general understanding. Knowledge becomes increasingly trapped in disciplines, and people outside a given discipline may become "logical aliens", i.e. they do not understand the logic and standards of a specific discipline: "if you are an academic employed by a university, and you want to meet a logical alien, you don't need to walk any further than the other end of the hall—or at most, to an adjacent building on your very own campus" (p. 33 in Millgram 2015).

Ways forward in academia

Dark knowledge is a challenge for democratic societies, as these need citizens who can make informed decisions. If people are ill-informed or do no longer care about the truth, democracy is at risk and science will basically become irrelevant (Kitcher 2011). To avoid such a pessimistic scenario, what are possible ways forward? Here, we focus on the academic realm and outline five approaches below (summarized in Fig. 4).

We do not explicitly mention public engagement of scientists in the following sections even although it is implicitly included in some of our suggested solutions. Engaging with the public, including having an open and active dialogue with stakeholders, is a key task of scientists, and we refer interested readers to publications where these have been treated in detail (e.g. Bucchi and Trench 2008, Nisbet and Scheufele 2009, Groffman et al. 2010, Smith et al. 2013).

Open science

Key components of open science are open access to scientific publications, open data, open source and open methodology (Kraker et al. 2011). Thus, open science directly tackles one of the key reasons underlying dark knowledge, namely inaccessibility of data and information. It is hence an important step forward.

However, there are also important challenges. First, the public availability of data such as health records, behavioral data or genomic sequencing information poses a threat for citizens from private companies and (future) governments alike. There has been much research on the possibilities of re-identification of anonymized data, and many examples of past misuse of such datasets exist (Ohm 2009, O'Doherty et al. 2016). Second, a thorough discussion is necessary on how to deal with private companies using datasets of public research institutions. Open public databases are paid by tax payers and may be an important source of wealth for private companies, which themselves do not typically share their data with the public, or if they do, these data are often biased (see above). In other words, open public databases essentially subsidize certain private companies. It is clear that an open science approach alone will not solve the challenges underlying dark knowledge, thus additional approaches are needed (see below).

Diverse evaluation systems

There is an increasing need to revise performance metrics of researchers and institutions. As briefly outlined above, an application of few quantitative metrics, focusing on money, publications and citations, constrains academic freedom and favors mainstream rather than outside-of-the-box research, thus promoting research biases (e.g. the Matthew effect). Furthermore, it may impede inter- or transdisciplinary research and even threaten entire disciplines, in which financial interests, overall number of publications and thus citations are low.

There is a clear need to diversify evaluation strategies. Researchers should not always be assessed with the same set of metrics, but different metrics should be applied depending on which type of researcher with which skills is needed at an institution (Weingart 2005, Arlinghaus 2014, Hicks et al. 2015, Jeschke et al. 2016). Otherwise, players (i.e. researchers and heads of institutions) are *gaming* metrics rather than focusing on their research. Indeed, maximizing metrics has become an end in itself for many researchers, which is not surprising when these metrics are continuously applied for their evaluation (Lawrence 2007, Hicks et al. 2015). For example, many researchers today primarily think about how they can acquire grant money and how they can get into a high-impact journal. If different metrics are applied by different evaluation committees, researchers may be less worried about maximizing certain metrics, as they do not know which metrics will be used in their case. They can then instead focus on actually creating knowledge.

An international Court of Arbitration for REsearch (CARE)

Another promising way forward would be to use existing codes of ethics and responsible conduct in science and research (e.g. www.esa.org/esa/about/governance/esa-code-of-ethics; www.ama-assn.org/delivering-care/ama-code-medical-ethics) and turn parts of them into binding rules (cf. Kaushal and Jeschke 2013, Alberts et al. 2015). Any violations of these rules could be dealt with at an international Court of Arbitration for REsearch (CARE). A similar system exists for sports where disputes on e.g. doping can be settled at the international Court of Arbitration for Sport (CAS). CAS has three courts (in Lausanne, New York and Sydney). Maybe it would be worth trying to have at least one for research as well, either in the form or a court or a similar type of entity (e.g. an international agency of research integrity).

Such an international entity would help setting standards and stimulate a cross-disciplinary discussion of what constitutes scientific misconduct and what does not (cf. Neuroskeptic 2012). Furthermore, it would ensure independent investigations und judgements of possible cases of misconduct. Such independence is not guaranteed if cases are investigated by research institutions where they occurred or by journals where a study was published. Although some countries already have such an independent entity (e.g. Austria or Sweden, www.oeawi.at, www.epn.se/en/start/expert-group-for-misconduct-in-research-at-the-central-ethical-review-boardstar), many do not. If an independent entity does exist at a national level, a higher-level, international entity could handle revisions of cases that could not be resolved nationally.

Advances in research synthesis

The primary goal of research synthesis is to gather, process and present complex data and information, so that they become better accessible. Indeed, we argue that advances in research synthesis are key for tackling dark knowledge. For example, systematic reviews and meta-analyses such as those performed by Cochrane (www.cochrane.org) have proven important to synthesize data and information. However, we need to take the next steps. A promising path forward is an atlas or map of knowledge that will allow people to have an idea where certain research is situated, and which lines of research and hypotheses are (dis-)similar to each other (Bollen et al. 2009, Börner 2010, 2015, Kitcher 2011, Jeschke 2014). Such a map of knowledge will allow non-specialists to better understand a certain discipline and quicker acquire its knowledge. It is similar to a regular map of a city that helps people to orient themselves.

Such maps or other synthesis tools can only be successfully developed if scientists of several disciplines and artists work together. For instance, information technologists and statisticians need to work with experts on the focal research questions and artists or designers, the latter making sure that the final product (e.g. an online portal) is aesthetically sound and user-friendly. Fortunately, such joint work on advanced research synthesis seems to strongly increase, see for instance work on visual analytics (Keim et al. 2010), sonification which turns data into sound (Hermann et al. 2011) or the above-mentioned advances in creating knowledge maps. Advanced tools for research synthesis can also help uncover and correct for biases, e.g. by considering potential interests of the funders of a study.

Training the next generation of researchers

Targeted training can also help reduce dark knowledge. Teaching centers for data experts and data managers are important (e.g., https://cds.nyu.edu, www.monash.edu/it/our-research/research-centres-and-labs/centre-for-data-science). We increasingly need inter-disciplinary courses that allow members of different disciplines to talk to and understand each other (Millgram 2015). Additional training is required in how to critically evaluate information and reduce questionable research practices. Specifically, courses could include analyzing different information sources and teaching methods on how to separate science from pseudoscience (Boudry and Braeckman 2012). They should address questions such as: What constitutes or should constitute our evidence base? What is the role of evidence-based knowledge in society and political decision-making? For example, the course "Calling Bullshit in the Age of Big Data" by Bergstrom and West at the University of Washington, which started in 2017, is a valuable way forward. Its aim is to teach "how to think critically about the data and models that constitute evidence in the social and natural sciences" (http://callingbullshit.org).

Training of future researchers should also build awareness that scientists are not immune against biases that influence their work. A profound understanding is necessary of what differentiates responsible research from questionable research practices (Neuroskeptic 2012, Sijtsma 2016). The latter do not necessarily imply intentional fraud but can include "p-hacking", for example by repeating an experiment until the desired statistical significance is reached or ignoring outliers in statistical analyses (Neuroskeptic 2012, Head et al. 2015). Such practices of "data cooking" are unfortunately widespread (Fanelli 2009).

Conclusions

We showed that most research investments are *not* done with the principal intention to increase public knowledge. In relative terms, government investments into research and development are decreasing, but industry investments are increasing. Thus, knowledge seems to become increasingly privatized. Given that few global players dominate knowledge production and curation, this development could be termed *oligopolization of knowledge*: when few know much, and many know little. To increase public knowledge, we need to develop and implement an array of tools. Some of these tools were sketched above with a focus on academia. Additional tools that for example increase public engagement and participation in science are clearly needed within and outside of academia to avoid an age of public ignorance.

Author contributions

JMJ and KT conceived the original idea and concept of dark knowledge. All authors contributed to further development of the concept. SL collected and plotted the data. JMJ drafted the first manuscript version, and all authors contributed to revisions.

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