Big data, mHealth and bias: an epistemological analysis

For a critical appraisal of artificial intelligence in healthcare: the problem of bias in mHealth

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Abstract:

Artificial intelligence and big data are more and more used in medicine, either in prevention, diagnosis or treatment, and are clearly modifying the way medicine is thought and practiced. Some authors argue that the use of artificial intelligence techniques to analyze big data would even constitute a scientific revolution, in medicine as much as in other scientific disciplines. Moreover, artificial intelligence techniques, coupled with mobile health technologies, could furnish a personalized medicine, adapted to the individuality of each patient. In this paper we argue that this conception is largely a myth: what health professionals and patients need is not more data, but data that are critically appraised, especially to avoid bias. The validity of data and the validity of inferences drawn from the data by algorithms are indeed a major epistemic issue, though rarely addressed as such by health professionals or philosophers of medicine. Considering the history of epidemiology, specifically the formation of the concept of bias, we propose three research priorities concerning the use of artificial intelligence and big data in medicine.

Keywords : Philosophy of medicine. Bias. Big Data. Artificial Intelligence. MHealth. Evidence-Based Medicine.

1. Introduction

Big data and artificial intelligence (AI) are more and more used in medicine, either in prevention, diagnosis, or treatment. As in science in general, big data techniques (or the use of AI techniques to analyze big data, such as machine learning techniques) would constitute a scientific revolution in medicine, or, in Kuhnian words, a “paradigm shift”[1]: the epistemology of big data would be radically empiricist and purely inductive, and not anymore deductive-nomological as in the classical model of scientific method. Big data analytics would be value-free or bias-free, and we would not need anymore to use samples to make epidemiological surveys as, in big data, the sample is supposed to include the whole population (n= all). Applied to medicine, this implies that, to put it quite abruptly, we wouldn’t need epidemiologists or medical doctors anymore: big data analytics could diagnose a disease or even predict it, and detect hidden correlations between variables.

In this article, we argue that this conception of big data and artificial intelligence is largely a myth, which could have bad consequences for medicine as a scientific discipline, and for patients’ health. To our opinion, the use of big data by techniques of AI is not free from bias and could produce systematic errors in the clinical practice of medical doctors. To demonstrate this point, we will focus on two main problems: first, the data and the problem of its validity; second, the inference drawn from the data by AI, and the establishment of correlations through the use of algorithms. According to us, the large amount of data is rather a problem than a solution. The property of bias is indeed that it is insensitive to the size of the sample, even if the sample is the whole population: this kind of error, which is systematic and not random, tends to accumulate and not to cancel with the increase of the sample.

To demonstrate these points, we will use examples from the contemporary use of mobile health (mHealth), i.e. the practice of medicine and public health supported by mobile or wearable devices such as mobile phones or smart watches. We'll show that the validity of the data and of the inferences drawn from these data are likely to be biased. Then, we'll demonstrate that the so-called revolution of big data does not solve the problems raised by E. Murphy[2] or D. Sackett[3] in the late 1970s about the validity of epidemiological and medical data, but probably increases them. In other words, what contemporary medicine needs is not more data or more algorithms, but a critical appraisal of the data and of the analysis of the data.

2. Artificial intelligence, Big data and bias: old win in new bottle?

Artificial intelligence has attained a remarkable growth in last decade: we now have decision making algorithms based on huge datasets in many industrial and commercial sectors, including the healthcare industry. Big data and artificial intelligence constitute without doubt a major breakthrough in the history of humanity, and especially in the history of science. According to R. Kitchin[4], we even have entered in the "fourth paradigm of science": science would be "exploratory", "data-intensive" and founded on "statistical exploration and data mining". Thus, the epistemology of big data is radically empiricist and purely inductive, and not anymore deductive-nomological as in the classical model of scientific method. Indeed, with Big Data, "there is no need for a priori theory, models or hypotheses", and "through the application of agnostic data analytics the data can speak for themselves free of human bias or framing, and any patterns and relationships within Big Data are inherently meaningful and truthful"[4]. Moreover, the problem of sampling bias is completely removed as we don't need to sample anymore: this is the famous "n=all". This means for example that, in an epidemiological study, the source population is equal to the target population.

Applied to medicine, this implies that we don’t need epidemiologists or medical doctors anymore, as “anyone who can decode a statistic or data visualization”[4] is able to diagnose a disease or even predict it. One more interesting characteristic of big data is that the problem of causation is pointless. As Anderson[5] puts it, “correlation is enough”: “correlation supersedes causation, and science can advance even without coherent models, unified theories, or really any mechanistic explanation at all”. In other words, “the data deluge makes scientific method obsolete”[5]. And the end of science could lead to the end of medicine as we know it. In other words, epidemiologists or medical doctors will soon be replaced by Artificial intelligence. This is for example what is happening currently in dermatology. A recent article [6] shows that a deep learning convolutional neural network largely outperform dermatologists in melanoma diagnosis. If dermatologists are still useful, how long will it last? Is the medical profession part of the professions which are replaceable by artificial intelligence? We argue that this is not the case.

The main reason why we believe that we still need physicians and epidemiologists does not concern the “big” of the “big data” but rather the “data”, specifically the quality and the validity of the data. Nowadays, there is indeed a tremendous amount of healthcare data monitored and collected which is waiting to be analyzed. Most of this data is unstructured (multimedia, graphical, textual etc.) and its original form is of low value because of random or systematic errors. For example, there is a great variety of sensors according to what brand of smart watches is used: we can thus imagine that the measure of heartbeat can vary according to the brand of the watch (systematic error) or according to the conditions in which it is used (random error, due for example to a variation of contact between the sensor and the skin). Moreover, if one of the major problems of epidemiological studies –whether observational, quasi-experimental or experimental – was the fact that they were underpowered, i.e. they did not have enough data. Conversely, the main problem with artificial intelligence and Big data analytics could be that they are overpowered, i.e. they have too much data. This combination of data of variable quality with overpowered tools of analysis could lead to invalid inferences and conclusions, and constitute a threat to the replicability and reproducibility of the studies. This opens debate for validity and the accuracy of these data set before they are used in scientific or clinical research. It is tremendously important (both from epistemic, ethical and legal point of view) to ask if these algorithms are biased or not.

By “bias”, we refer here to the epidemiological definition of this concept, that is the “systematic deviation of results or inferences from truth” or the “processes leading to such deviation”[7]. This systematic deviation is in general due to “an error (…) in the collection, analysis, interpretation, reporting, publication, or review of data”[7]. In the context of big data, this epidemiological sense of the word “bias” must be related to the moral or legal sense of “bias” which refers to a strong feeling or prejudice in favor of or against one group of people, which can lead to forms of discrimination towards such attributes as ethnicity, gender, status etc. This kind of discrimination, due to a statistical bias, is currently raising several ethical and legal issues in some countries where artificial intelligence and Big data analytics are used in the criminal justice system to predict crime or to assess the risk of recidivism, leading to unfair decisions of justice[8]. This situation is nearly the same in medicine, as people from racial minorities or women for example are underrepresented in most of epidemiological studies and randomized clinical trials[9] [10], which obviously biases the results.

This question of bias in big data and artificial intelligence, in a medical or non-medical context, has already been tackled by several authors[11–18]. What has not been noticed by the authors working on this subject is the surprising similarity with the situation that epidemiologists and clinicians faced in the 1970’s. In a context of “a crisis of medical care”[2] and criticisms about the lack of scientificity of medicine made for example by A. Feinstein [19] or E. Murphy [2], or about the lack of methodological standards in epidemiological studies, especially the case-control study[20], E. Murphy and D. Sackett theorize the modern concept of bias. Their aim was to warn about the risk of spurious correlations, the problem of validity of data and the more general issue of scientific inference. Thus, the definition of bias given by Murphy (“A bias is a process at any stage of inference tending to produce results that depart systematically from the truth”[2]) largely and explicitly inspired the definition given by Sackett (“Any process at any stage of inference which tends to produce results or conclusions that differ systematically from the truth”[3]), which itself inspired the definition given in the *Dictionary of epidemiology*[7]. The first methodological innovation made by Murphy and Sackett is to distinguish different “steps” (six for Murphy[2]) or “stages”(seven for Sackett[3]) of research in which “bias may enter the scientific process”[2]. For Murphy it goes from the “design” to the “reporting”[2], and for Sackett from “reading-up in the field” to “publishing the results”[3]. The second, and more important, methodological innovation is that they explain how a vicious circle can appear to distort the scientific truth : “All these factors conspire to distort the general belief about what has been demonstrated in a particular case and, since such a belief forms the basis of prior convictions for the judgment of future published work, and almost closed circle of bias may be perpetuated”[2].

The thesis of this article is that what has been done in medicine and in epidemiology during the 1980s and 1990s has to be done again, in a different perspective and probably with different methods, in the field of artificial intelligence and big data in healthcare. Before we expose what has to be done in this field, it is important to give an illustration of our thesis by applying the methodology of Murphy and Sackett to what is currently happening in mHealth.

3. *Bias in mHealth*

MHealth is the term collectively used for the use of smart phone and other sensory devices for monitoring or improving medical care[21]. The concept of mHealth was first introduced in 2000[22] and was at that time defined as “mobile computing, medical sensor, and communications technologies for health-care”. This concept has evolved to become the “4G Health”[23], defined as “the use of mobile devices equipped with wearable sensors in collecting health data and physiological signals, tele-consultation, delivery of health information to practitioners, patients, healthcare consumers and researchers, remote and real-time monitoring of vital signs such as heart rate and electrocardiogram, the direct provision of care as well as training and collaboration of health workers, etc.”[24]. This 4G health will probably be soon replaced by “5G mHealth”[24], even faster and more connected, with a lower cost, both from economic and ecological point of view, and made to create a kind of “mHealth ecosystem”[21] which combines the Internet of Things (IoT) and the use of artificial intelligence tools to analyze the big health data produced by this ecosystem. The promise of mHealth is thus to provide a real-time monitoring of the patient (but also of the healthcare system), and to transform “the current reactive medicine” in a “ proactive healthcare featured with diseases prevention”[24]. Moreover, mHealth appears in this context as one of the main tools of what is called P4 medicine, i.e. “predictive, personalized, preventive and participatory”[25].

The biggest strata of mHealth consumers use those apps for health care references, tracking fitness, diagnostics, disease management, etc., out of which most famous categories are fitness and disease management. One best example to all of these categories could be pregnancy term or mental health[26]. For example, the mHealth app for both the conditions would monitor user’s physical activity such as step count, sleep wake cycle, integration with the phone, calories, water consumed, reminder for medicines and tracker for mental wellbeing in terms of courses or multiple choose questions to keep a check on user’s day to day condition. Some of this data is recorded automatically; however, other needs to be recorded manually which could be a primary source of bias in mHealth care. Therefore, mHealth platform could be built on biased data, and this could open room for biased diagnosis and results which might potentially harm users. We can distinguish many steps or stages where bias can enter: during data collection, manipulation or processing, this last one being more difficult to discover. The problem is that bias can cumulatively increases at each successive level, without anyone being able to notice it. We can detail six stages where bias could enter:

(1) How the problem is defined[27]: this refers specifically to the definition of what counts as a success (or the preferred outcome) according to the developers of the algorithms when they train the algorithm in the case for example of a supervised machine learning algorithm.

(2) Social and technical intervention where certain type of data is incomplete or underrepresented, which might be a result of discrimination or unreliable circumstances (manual recording of data). Ferryman and Pitcan[28] showed that the mHealth ecosystem risks to bolster this cycle of underrepresentation. Majority of mHealth users tend to be young, prosperous, and educated. Their data is used to generate new insights that feedback the Machine Learning models. Biased data can impact validation (testing a model for accuracy), as well as model training. If accuracy is tested on a test set that under-represents minority groups, the resulting overall accuracy rates will not be true for those groups. For example, studies have shown that women face disparities in care; they are more likely to die of septic shock, for instance[29].

(3) Feature selection which could result in biased outcome when features (which are variables of data that factor an algorithm) are unevenly distributed across different groups. For instance, cardio-vascular disease progresses differently in case of men and women[30].

(4) Training of the model (as these models train from training data sets as well as labels given to the data) which could be highly variable and lack certain variables from data to data [31].

(5) Model Selection and accuracy: this refers to the capability of Machine Learning to understand how the algorithm makes decisions, for instance availability of hospital beds for the population depending on patients condition [32].

(6) Design of user interface or experience which opens room for various biased assumptions such as lack of directory for users, weak or no network, weak sensors etc.[33] "[and back to (1)]", as Sackett puts it in his article[3].

Thus, as machine learning algorithms are trained on data sets, and as the data set are prone to be biased for various reasons (under- or overrepresentation of a specific group, whether it concerns age, gender, ethnicity, etc.; great variability in the validity of the data due to users, sensors…), these algorithms are likely to be biased too. From a historical point of view, it is interesting to know that what is considered[34] as the first definition of bias given in the history of medicine and epidemiology, by Donald Mainland, refers to the idea of "mislabeling"[35], mislabeling that "may mask a real association as well as create a fallacious one"[36], and thus lead to fallacious conclusions in a clinical or epidemiological context. J. Berkson (and Mainland's 1953 article[36] was written to popularize Berkson's bias) is famous in the history for having demonstrating that the so-called correlation between diabetes and cholecystitis (which led surgeons to remove the gallbladder for the treatment of diabetes) was just a statistical artefact[37]. Yet, the problem is that a machine learning algorithm (for example, a machine-vision model to recognize a car or a road sign in the case of an autonomous vehicle, or a medical image processing to identify tumors) needs generally thousands of labeled examples to learn: if some of the original labels are biased, i.e. invalid, all the process is bound to be biased.

4. For an Evidence-based approach to big data in medicine: some research priorities.

The promise of AI and big data in medicine is to furnish a personalized medicine to all users, which would go from the genetic markers to the physiological constants, the dietary habits, the duration of sleep, the practice of sport, etc. of the individual. This is largely a myth because, as we saw, there is a high risk of bias at each stage of the data processing and analysis: the sensors, the human fallibility when entering a data, the training of the model, the user interface, or even the variability between the various operating systems of mobile phones or wearables devices. Upstream of the ethical and legal issues that big data and mHealth raise, such as privacy or risk of discrimination, there is an epistemic issue which is even more central. How can we know that the data is valid? How can we be sure that the algorithm is not biased? How can we guarantee that the association between a factor and a disease found by an algorithm is real and not spurious?

To be clear, there are no simple answers to these questions, and probably no good solutions. Having to face a growing medical literature and numerous medical scandals or failures (a long list of these failures can be found in J. Stegenga's *Medical Nihilism*[38], without even mentioning the famous and more recent article[39] written by J. Ioannidis stating that "most published research findings are false"), some physicians such as E. Murphy or D. Sackett decided to tackle the problem head-on through one main strategy. This strategy, which is qualitative, consisted in the critical appraisal of a medical article (first introduced by E. Murphy[2] in his penultimate chapter, called "An exercise in qualitative criticism"), and more generally, in the critical appraisal of the medical literature. Sackett and his colleagues thus decided to teach "the basic principles of critical appraisal to medical residents in 1978"[40] at McMaster University, which became an "annual international 'Critical Appraisal of the Medical Literature Workshops' for colleagues around the world"[40]. Then they extended "the Critical Appraisal concepts to include clinical decision making for and with individual patients": this gave birth to evidence-based medicine, defined later as “the conscientious, explicit, and judicious use of current best evidence in making decisions about the care of individual patients. The practice of evidence-based medicine means integrating individual clinical expertise with the best available external clinical evidence from systematic research”[41]. One of the most prominent progress in methodology that evidence-based medicine permitted is the hierarchy between various levels of evidence, from the expert opinion to systematic reviews and meta-analyses, the main criteria of hierarchization being the fact that the studies have been critically appraised or not. So, what physicians, healthcare professionals and of courses patients need today is not more data, or more algorithms, but, as Murphy said, an “alert common sense”[2] to assess the epistemic value of data and of algorithms.

In other words, what is needed is an evidence-based use of AI and big data in medicine. To do that, we can identify, such as Sackett did in 1979, three “research priorities”[3]:

- The first one should be to start a catalog of bias (“the continued development of an annotated catalog of bias”[3]), and to identify the magnitude and the direction of the various bias, as much as the stage of data processing (input, analysis, output) they enter. This is the only way to assess the validity of the data, of the algorithms and of every outcome of the reasonings of artificial intelligence.
- The second one could be the development of methodological standards for the use of big data and AI in a medical context: from an ethical and from an epistemic point of view, algorithms have to be “explicable”, as Floridi and Cowls[42] put it. What they call the principle of “explicability” refers both to “the epistemological sense of *intelligibility* (as an answer to the question ‘how does it work?’) and to the ethical sense of *accountability* (as an answer to the question: ‘who is responsible for the way it works?’)”[42]. This is particularly important in medicine and public health, where decisions are a matter of life and death.

- The third and last research priority is to develop a critical appraisal of artificial intelligence and big data in science in general, and particularly in medicine. The young movement of "Critical Data Studies"[43] seems promising and must be broadened to all scientific disciplines which use big data and artificial intelligence. This perspective of critical thinking on data must also be included in the education of professionals (healthcare professionals in our case), with specific courses about how artificial intelligence and algorithms work. This is the only way to cultivate some kind of skepticism and critical thinking about big data and artificial intelligence.

5. *Conclusion*

In a recent article published in *Nature*, S. Leonelli stated that "extracting knowledge from data is not a neutral act"[44]. The aim of this article was to show that it is impossible to agree with the idea that big data analytics would be value-neutral or bias-free. Moreover, the very much idea that numbers or statistics would speak for themselves is very dangerous, both from an epistemic and a political point of view: numbers, statistics or science in general never speak for themselves, and the history of the twentieth century has demonstrated that science could be used to justify the murder of million people. Concerning now the thesis that correlation is enough and supersedes causation, the history of modern epidemiology, especially the debate on smoking and cancer, shows that assessing the validity of a statistical correlation, which precedes the assessment of a causal relationship, is a very complex task. For example, the demonstration of the validity of the association between smoking and lung cancer took a long time and mobilized the most prominent figures of statistics and epidemiology, such as R.A. Fisher, J. Berkson, A. B. Hill, J. Yerushalmy, J. Cornfield, A. Lilienfeld, etc. Therefore, if a correlation is found by algorithms, it is not sufficient: the validity of this statistical association must be evaluated and critically appraised by scientists who are working on this subject. Then, if it is proven that the association is valid, it is possible to begin to assess if this correlation between variables is to be considered as causal or not, using the guidelines proposed by A. B. Hill[45]. But the evaluation of the validity of the correlation and of the causality can only be done by humans, and by specialists of a scientific discipline, namely epidemiologists and physicians.

Therefore, there is here an epistemic limit to big data and artificial intelligence: as artificial intelligence cannot explore its own cognitive and epistemic limits, it is the role of humans to do it. In other words, and contrary to what M. Minsky[46] thought, we maintain that "critical thinking" cannot be implemented into AI but is a property of the human thought. That's also why we still need physicians and epidemiologists: the ongoing pandemic of Covid-19 shows a good knowledge of research methodological standards and of the philosophy of medicine and epidemiology is absolutely necessary to make effective research[47] which could lead to a good treatment or a vaccine. If big data and AI are very powerful tools, they should stay a tool in the hands of the healthcare professionals and of the patients, who are the only one to be able to critically appraise the reasonings and outcomes of artificial intelligence artefacts, and to apply their knowledge to each particular situation, more efficiently than any "electronic hardware shop", as R. Thom said.[48]. According to Canguilhem, R. Thom, "who explored the difficulties of constructing models capable of approximating chance and of formalizing the unformalizable", also said that "in this task, the human brain with its old biological past, its clever approximations, its subtle aesthetic sensibility, is still irreplaceable and will remain so for a long time"[48]. This is even more true in the medical and clinical context, where the human relationship between a physician and his patient is fundamental.

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