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A genealogy of the ambiguous use of digital memory in machine learning and artificial intelligence

Abstract: This paper aims at a genealogy of the digital memory. The use of the same word for an electronic repository and for human skill produced a misunderstanding that caused the equivocal merge of two divergent concepts. Electronic data kept in a registry of information was interpreted like remembrances, recorded experiences, plus the capability of sorting out the right information when the quantity of stored data progressively available is too much. The more data was available the more machine learning techniques were compared to human cognitive processes necessary in understanding things and acting appropriately according to the acquired knowledge. Digital data retains a presumed 'purity' as the representing technical tool adopted to store information within a digital repository, whose name is always echoing a human faculty. The digital storage is, in fact, a 'digital memory'. The use of such a world involves a pretence of identity between the human memory and the memory of the artificial device and is a key factor in disguising the mediation layer, necessary to supplement the digital storage.

The paper argues that these prejudgments relate to the genealogy of the idea of digital data, as preserved in computer memory, or in a computer network memory. According to Norbert Wiener – the father of cybernetics – human memory can be reproduced in digital machines, provided there is enough space within it. According to Wiener the idea of memory is relative to the quantity of accessible data that can be stored in it. In his work he continues the project also suggested by other scientists – such as Alan Turing, Warren McCulloch and Walter Pitts, among others – that human memory's activity could be achieved perfectly well in the digital device, provided enough space is allowed for storing the relevant information.

This paper argues, instead, that data can only exist in accordance with a chosen interpretation and can be accessed through an implicit agreement on its inherent meaning, that strongly depends on quantification, measurement or on any other technique used to capture and organize it. Those interpretation choices are reticent, often unconscious, and always blurred inside the system.

The hypothesis that data gathering automation leads to a surplus of meaning, free of subjective judgment reinforces the autonomy of the system on a technical and symbolic level. It will be shown that this approach is not supported by valid epistemological arguments and that it involves a loss of control over the infrastructure of meaning, that could have retroactive effects also on human beings who should conform and obey to rules that they could not regulate or determine.

Mechane, n. 2, 2021 • Mimesis Edizioni, Milano-Udine Web: mimesisjournals.com/ojs/index.php/mechane
• ISBN: 9788857589282 • ISSN: 2784-9961

1. Setting the scene

This paper aims at clarifying the concept of Big Data, and its connection with the idea of the externalization of memory that produced the start of the digital revolution. The project consists in investigating whether it is legitimate to assess the hypothesis that human memory could be perfectly reproduced and simulated by a digital repository, without losing any of its characteristics in terms of selecting and reproducing relevant information acquired in different contexts and moments in time.

The idea of digital memory, put forward by the pioneers of the general-purpose computing machine and cybernetics, assumed that all the functions of human memory (including sorting and selecting data for a specific decision) could be implemented within the large data repositories that are implemented in digital machines (Numerico 2017).

Norbert Wiener (1961, 1954), Joseph Licklider (1960) and Robert Taylor (with Licklider 1968) shared the idea that the computer – a digital stored-program machine – would be able to undertake or to support certain human tasks by externalizing the functions of human intelligence, especially with regards to memory. The availability of a quick, basic way to manipulate information, combined with a huge amount of data would transform the communication and acquisition of knowledge.

This conception of digital communication technologies was inherited by cybernetics, among other disciplines, and it was established on the implicit belief that it was possible to capture human intellectual/cognitive capabilities, substituting the intuitive, and responsible human decision taking by a quick sequential processing of a massive amount of data. Wiener himself, however, was rather scared about the social and political consequences of this new transdisciplinary approach to knowledge, that he called cybernetics.

This paper argues instead that data can only exist in accordance with a chosen interpretation and can only be accessed through an implicit acceptance of its inherent meaning, which strongly depends on quantification or on any other general technique through which it may have been captured (Drucker 2011; Rouvroy, Berns 2013). As already suggested by Lewis Mumford (1970), once we decide to focus on quantity, we have already changed our hermeneutics radically (Rockwell, Sinclair 2016). The idea that data gathering automation leads to a surplus of meaning, free of subjective judgment, reinforces the autonomy of the system on a technical and symbolic level. It will be shown that this approach involves a loss of control over those systems, which govern all meaningful processes, and transform their human users asking for their compliance and obedience.

Next section is dedicated to the birth of this new discipline, considering the epistemological effects on the definition of communication and control phenomena under investigation.

2. Memory and feedback in cybernetics

Cybernetics, the discipline that Wiener invented during the Forties of last century, was based on two pillars. The first one was relative to the idea that communication and control were intertwined notions, because control was a special case of communication, in which those who emit the message wanted to check that the message was understood and accomplished by those to whom the message was directed. The second pillar was related to feedback, "the property of being able to adjust future conduct by past performance. Feedback may be as simple as that of the common reflex, or it may be a higher order feedback, in which past experience is used not only to regulate specific movements, but also whole policies of behavior" (Wiener 1954, p. 33).

Memory and feedback are correlated notions because for feedback to take place we need to use the results of past performances to modify the future behaviors. It is, then, necessary to retain memories of past events, stimuli, and messages. Wiener was convinced that there were different types of feedback. In some simple cases those interactions were based on numerical data that were used for "the criticism of the system and its regulation" as in control engineers' activities. However, there were more complex situations in which "the information proceeds backward from the performance is able to change the general method and pattern of performance" (p. 61). In these contexts, the process which takes place can be considered like learning.

This approach to feedback implies a transformation on the concept of memory. Negative feedback requires that the environment stimuli together with the previous behavior habits of the agent should be recorded somewhere inside the system. High level feedback presumed that it was possible to retrieve, manipulate and adopt previous information, by selecting the useful one to change the behaviors of the agent, adapting it so that it produced a general transformation, as it usually happens in learning phenomena.

This was described as a general process that could happen indifferently in human beings or in machines, provided that the right feedbacks phenomena were available to the learning agents. The term memory, thus, referred indifferently to the human capacity to remind thoughts, to collect memories and to use those skills to sort out the best insights to be adopted in a new context, as well as to the capacity of the machine to execute the correct instructions and to react appropriately to the information used as input in the feedback negative circle. The most common metaphors in the work of Wiener were based on war examples because he experiences the feedback model while he was involved in designing prediction machines for anti-aircraft fires during the Second World War. The principal reference model for Wiener then was the teleological behavior of weapons that had to reach the target.

> Wiener came to see the predictor as a prototype not only of the mind of an inaccessible Axis opponent but of the Allied antiaircraft gunner as well, and then even more widely

> to include the vast array of human proprioceptive and electro-physiological feedback systems. The model then expanded to become a new science known after the war as "cybernetics," a science that would embrace intentionality, learning, and much else within the human mind (Galison 1994, p. 229).

The thesis of Peter Galison – a scholar member of the Stanford School[1]– was that war transformed each enemy in a mechanical agent:

> On the mechanized battlefield, the enemy was neither invisible nor irrational; this was an enemy at home in the world of strategy, tactics, and maneuver, all the while thoroughly inaccessible to us, separated by a gulf of distance, speed, and metal. It was a vision in which the enemy pilot was so merged with machinery that (his) human-nonhuman status was blurred. In fighting this cybernetic enemy, Wiener and his team began to conceive of the Allied antiaircraft operators as resembling the foe, and it was a short step from this elision of the human and the nonhuman in the ally to a blurring of the human-machine boundary in general (Galison 1994, p. 233).

If the enemy was not a human being, but an agent strictly intertwined with a machine, then also allied forces were like him. On the battlefield it happened an elision, a blurring of the borders between machines and human beings. The hypothesis behind this belief was described in Wiener's seminal book *Cybernetics: Or Control and Communication in the Animal and the Machine* (1961 [1948]), and in a paper published in 1943, *Behavior, purpose, teleology* (written with Arturo Rosenblueth and Julian Bigelow). Their aim was the definition of natural events from a behavioristic point of view, concentrating the theoretical effort around the concept of purpose. The behaviors of machines resemble those of living beings because they were purposeful since they both implied negative feedback mechanisms. The authors adopted a classification of actions that allowed them to emphasize the centrality of purpose and teleology which "reveals that a uniform behavioristic analysis is applicable to both machines and living organisms, regardless of the complexity of the behavior". The thesis of the paper was that between animals and machines there was "a considerable overlap of the two realms of behavior" (Rosenblueth, Wiener, Bigelow 1943, p. 4).

In conclusion the paper stated that:

> A further comparison of living organisms and machines leads to the following inferences. The methods of study for the two groups are at present similar. Whether they should always be the same may depend on whether or not there are one or more

1 The *Stanford School* is a school in philosophy of science that argues in favor of a pluralistic interpretation in science. It is against the idea of science as a unitary enterprise. The original members of the school were trained or taught at the Stanford University during the Eighties and the Nineties. The theses of the group were concentrated on the pluralistic nature of scientific models and on a post-positivistic approach, based on the analysis of scientific work practices.

> qualitatively distinct, unique characteristics present in one group and absent in the other. Such qualitative differences have not appeared so far (Rosenblueth, Wiener, Bigelow 1943, p. 4).

The basic idea behind cybernetics was the possibility of investigting the behaviors of animals and machines by following the same lines of research, because there was no evident difference between the two. It was also likely that in the future negative feedback mechanisms of animals could be emulated if they followed the same processes: “the machines devised so far have far from exhausted all those possible modes”. Of course, it was clear that there were functional differences between animals and machines due to the different materials in their structures (colloidal and protein molecules in animals, while machines were largely metallic), and their dissimilar approaches to the use and storage of energy, etc. But according to the 1943 paper, these differences seemed little more than a minor blip than anything substantial.

Cybernetics thus bypassed all possible differences between animals and machines by offering a unified explanation of their activities based on scope and teleology, considering that those capabilities oriented to a purpose were as deterministic as all other behaviors.

Teleology was not linked to intentionality but to the mere technicality of being oriented towards a purpose, whether conscious or unconscious. There was a reciprocal interaction between the objective to be reached and the consequent act to accomplish. This reciprocity was not of causal nature but was rather framed within the coordinates of time and space. The activities and feedback systems sought an adequate response to reach a set purpose in a specific environment.

The “pre-scientific” hypothesis of cybernetics was that it was possible to compare living beings and machines in terms of their communicative expectations. The procedure that laid behind this reasoning was complex as well as linear. Firstly, any implicit relationship between different elements inside and outside of nature was interpreted as an exchange of information, characterized as data analysis. So, birds processed information about wind streams to facilitate their flight, reducing the energy needed to remain in the air resembled radars that processed data to determine whether an enemy plane was entering a protected zone. All signals were identical and captured in a space called memory or repository indifferently.

Every interaction was thus understood as an exchange of structured data that was processed and interpreted as signals needed for the established scope of the process. The teleological program of cybernetics implied a transformation of all signals, whether natural or artificial, which were represented as symbols encoded and analysed within the chosen system to achieve a desired result.

This transformation of information signals involved the assimilation of all possible interactions between living beings, devices, and the environment.

Cyberneticians thus decided to concentrate their efforts on understanding the similarities, while disregarding the differences. This attitude also influenced the use of the term memory indifferently in denoting both the human being faculty and the repository infrastructure of digital devices, such as electronic machines, disregarding the many distinctions of the two concepts.

3. Memory and measurability: value capture and human agency

The role of cybernetic rethinking of memory and the epistemological organization of closed box scientific models[2] had a profound impact on the idea of datification and on the consequent reorganization of many scientific discourses[3]. This section will focus on social science applications of big data tools.

Memory plays a central role in obtaining intelligent results using digital systems. For example, the *Cambridge Handbook of artificial intelligence* (2014, Ch. III) states:

> Use of memory would seem to require representations, and these representations must have their effects on behavior independently of the time at which the memory representation was created.
> …nonetheless, it is not plausible that there will be devices that will be widely accepted as exhibiting … intelligence but do not rely on memory.
> It is, however, not clear how this can be done without returning us to the previously discussed questions about how representations can be processed to yield intelligent outcomes.

This suggests that is like a balancing act to strictly connect the management of a huge amount of information within a repository and the ability to extract the right information from it when needed. Intelligent human tasks do not require learning by rote huge amounts of data, but they do connect heuristically information learnt from past experiences.

According to Wendy Chun the need for a huge repository of data betrays the desire for stability: "The desire to expunge volatility, obliterate ephemerality, and neutralize time itself, so that our computers can become synonymous with archives. These desires are key to stabilizing hardware so that it can contain, regenerate, and thus reproduce what it stores" (Chun 2011, p. 139). It is this desire to control and guarantee the truth of information and its stability over time that finds its niche in the archival capability of an externalized memory. While human memory

2 The concept of closed-box model was developed in another paper (Rosenblueth, Wiener 1945) in which the two authors discussed the epistemological use of models in science, by defining the process of science making as a progressive use of the concept of closed-box model, in which not all variables in the considered problem were explicitly treated. Some of them remained obscured and blurred in the closed box of the models. Such a concept is similar, though with some distinctions, to the later concept of black box in science developed by Latour in his work on Actor-network theory (1987).

3 For more details about closed box models in science see Numerico 2021, chapt. 1.

is fluctuating and unreliable, hardware memory always honours our expectations of stability (unless it breaks).

However, according to Chun, the expectations of the veracity and stability of memory in the digital environment is destined to falter, both because the hardware is fragile and tends to break very easily and also because the information kept in the database is full of noise and false information.

We use the maps offered by content management systems such as social network, chat services, email services, search engines, micro and macro blogging platforms, ecommerce platforms, social networks etc. by dwelling within their frames, but by doing so we change the meaning of their mapping. At the same time these platforms try to make sense of our presence within their spaces by remapping users' presence within their models and maps. Within this complex itinerary, our data becomes dirty and unreliable.

> These databases, which drive computer "mapping" / machine intelligence, become "dirty," unreliable, when they do not actively erase information: they become flooded with old and erroneous information that dilutes the maps they produce. Deliberately making databases dirty – by providing too much or erroneous information – may be the most effective way of preserving something like privacy (Chun 2011, pp. 93-94).

It is likely that the traces left by our clickstream and the data we disseminate in our online life are full of incongruences and ambivalences that resemble our emotional life and our relationships with desires, fears, and unconscious drives. Our online behaviors (and sometimes also the offline habits) reflect our confused passions and emotions and are difficult to interpret or understand. Why do we trust the capability of machine learning tools to decrypt and clarify our future intentions, based on our past habits?

The elevated speed of the machine is limited by the type of operations it can perform. The machine is a number-crunching device, able to overcome its own limits whenever it is upgraded with a new processor or memory, or increased bus or network speed. However, it can deal only with numbers and instructions that are very clearly stated: they must be formalized in a language that can be compiled or interpreted in machine code. This is the formulation problem[4]. The limits of computation cannot be underestimated. The abstract model of the machine was invented to demonstrate a limitation of the system of calculation within mathematical logic: the *halting* problem (Turing 1937). It is impossible to know when and if a program will stop once we launch it, and there is no way to know the response in advance. The practical machine, moreover, has other limits; it can deal only with finite mathematics or with problems that can be completely formalized. All the rhetoric of artificial intelligence, deep learning, or machine learning algorithms cannot take the machine outside of these limitations.

4 See Passi, Barocas 2019 for more details on this issue.

According to Wiener, for example, cybernetics, though considered a transdisciplinary field, could not give interesting results when applied to society because “For a good statistic of society, we need long runs *under essentially constant conditions* …Thus the human sciences are very poor testing-grounds for a new mathematical technique” (Wiener 1961, p. 25). He was sceptical that mathematical measurements of feedback effects could produce interesting results because the fluctuations of variables that influence the phenomena under investigation were too hard to identify or specify in a mathematically rigorous way. It was better, in his opinion, to deploy methods in the fields that allowed a clearer formal description of the relevant models of the phenomena. His belief, however, was less influential than the cybernetics ideology that was implied in his research, despite his will.

4. The dangerous desire for classification and categorization

The desire for categorization of human behaviors together with the need for a stable set of methods to define problems and suggest solutions in the social sciences was the cause for disregarding the suggested critics about the use of statistical methods for understanding and anticipating human agency in terms of beliefs, desires, intentions, supported by the data deluge. According to Bowker and Star (2000) the need to classify and organize is human, and cannot be avoided. But it also must be kept in mind that categorizations and its resultant representations of social phenomena were the results of a struggle of powers. The struggle lies in defining a list of categories and imposing them on a domain of subjects in ratios decided by the winners. Categorization is always the result of a hard negotiation. When the machines are included in the negotiation, as suggested by Pasquale (2015), O’Neil (2016) and Chun (2016), another opaque and secret layer is added to this already blurred mediation between powers. It is impossible to measure or evaluate all the variables that together define the character of a person, or may help in anticipating his or her behavior. However, the drive for clusterization leads to the establishment of fixed rules that determine and predict the habits of people, by including their observed reactions within predetermined profiles.

This approach obliges researchers to exclude many relevant variables, because they are too awkward, too intertwined, or immeasurable. So, it does not matter if they contribute to the evaluation of a subject: because if they cannot be formally defined, they cannot be used.

Cabitza and his research group (2017) pointed out that a machine learning-based decision support system could have a negative impact when applied, for example, within the field of medical diagnosis. First, these data-intensive methods are fed with information that can only be represented in a textual form. Every contextual information on patients could not be described precisely and must therefore be disregarded. This can produce misleading evaluations in giving diagnoses. These systems “bind empirical data to categorical interpretation”, although in medicine not all observers agree with each other on diagnoses. According to the paper: "This observer variability is related not only to interpretive deficiencies, but also to an intrinsic ambiguity of the observed phenomena" (Cabitza *et al.* 2017, E2). So it is inadequate to rely on systems that are unable to take into account the variability and ambivalence of clinical diagnostic findings. There are intrinsic uncertainties within medical science that need to be taken into account, while data-driven machine learning-based decision support systems are unable to manage uncertainty, due to their need for "data accuracy and completeness" in order to formulate a credible hypothesis. In health problems we can see the undesired consequences caused by the substitution of human memory (represented by the uncertain and incomplete patient records, produced by doctors and nurses) with precise digital descriptions of the patients' conditions, consisting of perfect univocal textual data, not influenced by any implicit context.

Everything the machine can process must be measurable, and when the quantification of the phenomenon is problematic it is mandatory to find a way to produce the quantitative assessment with the corollary method for standard definition and category attribution, no matter how many unsought outcomes are produced. A univocal quantification is vital for the success of a deterministic machine designed to produce a quick output as a solution to a problem.

An example of the unfair results produced in the health field, by this attitude can be found in a paper that deals with mortality prediction in cancer patients, according to which machine learning algorithms were able to outperform random and other prediction strategies by including in the analysis some data relative to demographics, social, racial, and other personal characteristics of patients

> A machine learning model based on single-center EHR data accurately estimated individual mortality risk at the time of chemotherapy initiation. The model performed well across a range of cancer types, race, sex, and other demographic variables. Mortality estimates were accurate for palliative as well as curative chemotherapy regimens, for early-and distant-stage patients, and even for patients treated with clinical trial regimens introduced in years after the model was trained. Our model dramatically outperformed estimates from randomized trials and SEER data, both of which are routinely used by clinicians for quantitative risk predictions (Elfiky *et al.* 2017, p. 12).

We must inquire which is the aim of this research. Is it to improve the conditions of people whose demographic variables show that they are weaker or poorer than the average population, or will it be used in practice to evaluate the mortality risk of patients and avoid treating them if their mortality prediction is too imminent? The objective of such study seems to legitimate a form of discrimination about making medical decisions on people of low income, on worse insurance programs, or of Afro-American, or Latinx origins, to save money for a national health system or for a private health insurance company. The probability evaluation inferred is established on a categorization of inequality described as an inevitable destiny for some group of people. In the meantime, this unfair perspective is distorted within the rhetoric of the algorithms as powerful, magical tools for anticipating events, while in fact they are creating a brand-new control which acts in terms of biased *care management* solutions that we are obliged to accept (Finn 2017, ch.1). This blind belief on the power of algorithmic decision taking is sometimes called ‘enchanted determinism’ (Campolo, Crawford 2020). By this ideological strategy it is possible to disguise the explicit brutality of the social project: why should we spend money to take care of already fragile people, whose survival hope would be minimal? The bare formulation of the system’s purpose, hidden inside the algorithms chosen for the death prevision, end up in discriminating people, by defining the algorithmic objective and formulation of the problem pretending that it was a neutral evaluation.

5. The politics of memory, algorithmic opacity and its discontents: some final observations

The materiality of Big Data is intertwined with the concept of a new infrastructure and of a reorganization of memory. The new scenario brought about by the adoption of Big Data as the privileged point of view has led to the creation of a cultural reorganization of memory for the acquisition and dissemination of knowledge, based on new values.

According to Beer “It is by acknowledging the long history of the accumulation of data about individuals and populations that we can begin to make a departure into seeing the different ways that data are presented in conceptual terms – and thus where we might begin to see more clearly the importance of the project of exploring Big Data as an interweaving of a material phenomenon and circulating concept” (Beer 2016, p. 4).

The new project is the representation of all kinds of phenomena through data. This leads to a double-edge situation: on the one hand we have the problem of how to deal with the resulting data deluge; on the other hand a wide variety of phenomena must be transduced into data for algorithms to make sense of them. As an example of the cultural and social governance of phenomena through data representation and measurement, Beer (2015) discusses the use of productive metrics in the game of football. The algorithms that measure players’ performances play a key role in the recruitment market and in team selection. According to Beer:

> Football provides us with illustrative examples of ‘the politics of data circulations’ (Beer 2013). It also provides further illustration of how data circulations reshape culture. We can readily see how metrics fold-back, in feedback loops, reconfiguring the structure and form of the game itself, whilst also potentially reconfiguring how it is consumed (Beer 2015, pp. 9-10).

Beer adopted the notion of productive metrics to show how much we trust them to discover and exploit hidden talents. Value is produced through the bare introduction of metrics, when combined with suitable evaluation practices. The procedure is similar for both athletes and academics and depends on inputting the right statistics.

As suggested by Gillespie (2014) algorithms used in Big Data are combined with a database that is structured to obey their needs: "before results can be algorithmically provided, information must be collected, readied for the algorithm, and sometimes excluded or demoted" (2014, p. 169). In other words, it is impossible to interpret an algorithm without considering carefully its relevant data, including the training set. This amounts to another layer of complexity needed to understand the functioning of an overall system consisting of both algorithms and the data structured to work inside the systemic frame of meaning. It also increases the likelihood of mistakes, manipulations and misunderstandings of phenomena represented by the data. Individual interpretations are hidden among these strata of multiple representations and reorganization of data, sometimes without the explicit awareness of the researcher. However, interpretation is still active in the biases and prejudices embedded in the cleaning and organizing of data as well as in the anonymous and deceptively neutral rules as implemented by the algorithm.

One of the key things worth mentioning in relation to Big Data and its organizing algorithm is that we must understand: "For whom, besides insurance companies, is this correlation – the revelation regarding mutual habit formation – useful? These studies … are not designed to foster justice" (Chun 2016, pp. 14-15). This point touches on what Bernard Stiegler calls the philosophical problem of the politics of memory.

> The question of hypomnesis is a political question and the object of a struggle: a struggle for the politics of memory and, more precisely, for the formation of lasting hypomnesic environments. The exteriorization of memory and knowledge in the hyperindustrial stage is both what extends their limitless power and what allow them to be controlled. … All this fully sets in place a question of a biopolitics of memory (Stiegler 2006, p. 20).

The idea of Stiegler is that there is no interiorization that preceded the exteriorization of memory, but that the choice of media and methods of externalization must be regarded as the effects and the causes that belong to the realm of political policy. The history of humanity is, according to Stiegler, a story of the tools adopted to externalize memory and to keep track of acquired knowledge. From this perspective, there is nothing intrinsically wrong in the process or exteriorization itself. However, if the capture of exteriorized data has a predatory character, it will be difficult to prevent nefarious consequences for its violent appropriation.

According to Rouvroy and Berns (2013) there is a kind of government based on algorithms, which promises to be completely neutral in the imposition of statistics over the complex and unstable virtual individualities of people. This is promoted as (a-)normative rationality, which is based on collecting, aggregation, and the automatic analysis of data in such quantities that it can be used to preview and anticipate possible behaviors.

In the introduction of a special issue of *Big Data and society* dedicated to the issue of critical data studies, we read: "The application of social solutions to increase data literacy and justice involves effecting change by conducting research and sharing that research and the activities that might grow out of it with the public. … By maintaining these orientations and principles, Critical Data Studies should encourage us to think about Big Data science in terms of the common good and social contexts" (Iliadis, Russo 2016, p. 5).

We need to open the black box and to analyse the principles and biases embedded in the processes of both data collection and data cleaning, and in the management of algorithms that process that data. The problem of intelligent (i.e. machine learning and deep learning) algorithms is that we always think that the methods can arrange data in a neutral and smart fashion, when in fact algorithms are written by programmers and only allow machines to do what they are prescribed to do (Tufekci 2015).

Looking at Big Data science in terms of representation and intervention (Hacking 1983) we need to make clear exactly how data represents social phenomena and how algorithms permit us to intervene and understand them and whether we really need such an intervention. It is crucial to keep in mind firstly that the agency of the machine is not moral in nature, and secondly that the speed of the machine is incommensurable if compared with a human being (see. Floridi 2012; Numerico 2021 for more details on this issue).

As already pointed out by Wiener (1960), attributing the responsibility of decision-making to the machine can result in unforeseeable risks, and there is insufficient time to prevent the consequences of the decisions, once that mechanism is already in place. Although the conclusion of Danaher (2016) on the potentiality of a governance based on algorithms is overly pessimistic, his analysis of the risks of an attitude of complete submission to algorithmic decision-making is more to the mark. It is crucial not to hand over to the deterministic view of technology and its effects on society. There are still grounds for optimism since the closed box can be opened and the true objectives of data processing through algorithms can be uncovered. Keeping in mind the genealogy of the Big Data *techno-solutionism* rhetoric (Morozov 2013), it is possible to contrast the excesses of intervention on political and social decisions based uniquely on the data and guided mainly by algorithms. Understanding the policy of digital memory and primarily who enacts it, who gains from a specific representation of, and intervention into people's social and personal habits will shed light on the consequences of any prediction of those supposedly recorded habits. We need to define and pursue an epistemological strategy for a systematic opening of the black boxes of the Big Data representation of social phenomena, and of the algorithms organization of problems solutions. The present paper proposes a starting point in the creation of such a strategy, by defining the genealogy of the development of the fetishization of data as a policy of memory and of software or algorithmic machines as a proposed universal organization of knowledge.

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