Artificial Communication?
The Production of Contingency by Algorithms

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1. A sociology of algorithms

Algorithms are social agents. Their presence and role are now central and indispensable in many sectors of society, both as tools to do things (as machines) and as communicative partners. Algorithms are involved in communication not only on the web where the active role of bots is now taken for granted, but also (explicitly or not) in more traditional forms, as print communication and even voice communication.

Precise estimates are difficult (Ferrara et al. 2016), but apparently in online communication bots are the authors of approximately 50% of the traffic[2]. Millions of Twitter users are bots[3], more than 70% of trading in Wall Street happens via automatic programs, at least 40% of Wikipedia editing is carried out by bots. Highly automated accounts generated close to 25% of all Twitter traffic about the U.S. 2016 presidential debate (Kollany, Howard and Woolley 2016). That Google and Facebook are driven by algorithms is well known, with the paradoxical consequence that the "discovery" that human operators guide the selection of news in Facebook Trending Topics was perceived as a scandal (Gillespie 2016). Similar systems are also used in personalized communication: on Gmail, the app Smart Reply recognizes emails that need responses and generates perfectly adequate natural language answers on the fly[4]. Spotify's most popular compilation, Discover Weekly, is entirely assembled by an algorithms - as well as Release Radar, the hyper-personalized playlist of new tracks (Pierce 2016b).

In these and many other cases web surfers communicate with algorithms, and often this happens also when we read texts in the traditional form of newspaper articles or books.

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[1] This text is an expanded and revised version of the inaugural lecture of the Niklas Luhmann Guestprofessorship 2015 at Bielefeld University. For comments, criticisms, and suggestions on an earlier draft of this paper, I would like to thank David Stark, Alberto Cevolini, Giancarlo Corsi and the anonymous referees of *Zeitschrift für Soziologie*.

[2] Global Bot Traffic Report 2015

[3] According to the company itself, which provides its users a tool, Twitteraudit, to calculate how many of their followers are "real" (meaning human beings).

[4] https://gmail.googleblog.com/2015/11/computer-respond-to-this-email.html

Companies like Narrative Science[5] and Automated Insight[6] have developed algorithms to produce texts that are indistinguishable from those written by a human author: newspaper articles, brochures for commercial products, textbooks and more. Philip Parker, professor at INSEAD in Fontainebleau, patented a method to automatically produce perfectly plausible and informative books, including more than 100,000 titles already available on Amazon.com. Robo-journalism is regularly used by The Associated Press and many companies like Samsung, Yahoo, Comcast and others (Podolny 2015).

Even in voice communication, millions of individuals regularly interact with digital personal assistants like Apple's Siri, Amazon's Alexa, Microsoft's Cortana, IBM's Watson or Google Now, using natural language interfaces to answer new questions, manage the calendar, offer individual suggestions and recommendations. In many cases, these programs seem to know the users better than their human partners and often better than the users themselves (Youyou, Kosinski and Stillwell 2015), anticipating their needs and demands even before they emerge.

The communicative role of algorithms is clearly a massive social phenomenon with many complex consequences. What has sociology to offer on this topic? Marres and Gerlitz (2017) denounce a social deficit of computational technology, because in the discussion to understand these developments and to provide an interpretive framework, social sciences and sociology are curiously in a secondary position. Certainly there is a lot of sociological work on the social consequences of the spread of digitization, but it often follows developments that take place and are established without its contribution. Social sciences are committed to identifying shortcomings and dangers of technology. In highlighting the ethical and political aspects of technology and its impact on public opinion or social order, they focus on issues such as threats to privacy, risks of job loss, concentration of power in a few large corporations, intergenerational or international inequalities (digital divide), the exploitation of underpaid workers (Mechanical Turk) or even of all users ("If you are not paying for it, you're not the customer; you're the product being sold").

Why social deficit? The topics covered by social sciences are extremely relevant and their contribution very useful, but this does not exhaust the role that sociology could (and should) play in the development of digitization. The sociological perspective is not involved

[5] Cf. https://www.narrativescience.com
[6] Cf. https://automatedinsights.com

in designing algorithms, that are programmed without adequate consideration of social and communicative aspects. The reference is still to individuals, as in Artificial Intelligence (Nilsson 2010): the goal is to artificially reproduce the abilities of human beings, possibly integrating cognitive skills with intentionality or with subconscious aspects identified by philosophical reflection (after Dreyfus 1972 or Searle 1980). In sociological perspective, however, the primary reference is not to individual psychic processes but to communications. After all, what is interesting in the interaction with algorithms is not what happens in the machine's artificial brain, but what the machine tells to its users and its consequences. The problem is not that the machine is able to think but that it is able to communicate. The reference to communication and social context is the central issue, which should primarily inform the programming of effective social algorithms[7]. Sociology is the discipline dealing with it.

This is especially urgent now, when algorithms massively and autonomously play a role in communication. With respect to the reflection on intelligent machines in the 1970s and 1980s many things have changed. First of all that computers are not isolated but always interconnected, and then that the connection happens through the Web 2.0, which includes previously unthinkable data sources. The participatory web invites users to generate their own video, audio and textual contents, which they share with other users in blogs, social media, wikis, and in countless media sites. This multiplicity of spontaneous and uncontrolled contents, with their metadata, adds up to institutional content and to the data provided by pervasive sensors (the Internet of Things) to generate the increasing mass (or cloud) of data available in digital format.

Availability of data, however, is not enough. Excess of data has rather always been a difficulty. But recent programming techniques are able to obtain and process data in ways that are vastly more efficient, and can also turn into advantages the problems that until now hindered the development of Artificial Intelligence projects, such as vagueness and messiness of data or the unpredictable variety of contexts. Self-learning algorithms are able to work efficiently with data that not only are very numerous and complex, but also lack a structure recognizable and understandable for human logic. Hence the recent (and far from clear) discourse on Big Data (Crawford, Miltner and Gray 2014), departing more and more

[7] Some isolated voices signal it since decades: cf. Suchman 1986; Collins 1990; the "socionics" project in Malsch 2001.

clearly from models referring to individual mental processes. Data are social in their origin, and the processes elaborating them are often incomprehensible to human observers.

To address these developments, I argue, we need an approach referring not to intelligence but directly to communication. This requires a powerful and flexible concept of communication, sufficiently independent from individual psychic processes and able to take into account the cases where the partner is not (or can be not) a human being. Such a concept must refer to society, not to individuals or groups of individuals[8]. I propose the theory of social systems in Niklas Luhmann's formulation as an adequate framework, with sufficient complexity to deal with these issues - although Luhmann himself did not work specifically on communication with algorithms.

In my argumentation I will first present the alleged Big Data revolution, which I attribute to artificial reproduction not of intelligence but of communication. Recent "smart" algorithms, I will show, are so efficient not because they have learned to work as human intelligence, but because they have abandoned the attempt and the ambition to do so and are oriented directly to the forms of communication. I then reconstruct the interaction with algorithms in the terms of Luhmann's theory, where the central point for the definition of communication is not sharing of thoughts among participants but presence of a situation of double contingency. I reconstruct from this perspective the communication with a partner who does not think, as a machine or any device capable of producing surprising information, and introduce the notion of virtual contingency to describe the situation in which a communication partner is confronted with his own contingency, revised and reflected in such a way as to simulate the conditions of communication. The real novelty of communication with self-learning algorithms, however, goes further: it is an unprecedented condition in which machines parasitically take advantage of the participation of users on the web to develop their own ability to communicate competently and informatively. They develop their own contingency, which I describe in the final part of the paper referring to the interplay between human capabilities and "creativity" of algorithms. It can be observed in AlphaGo, the computing system programmed to play the ancient game of GO. In the conclusion, the question whether the concept of communication can be extended to interaction with algorithms or a different concept is needed remains open, but I claim that in

[8] Marres and Gerlitz 2017 observe the need of a science of society as a consequence of the intensification of socio-technical infrastructures.

any case the discussion on smart algorithms should refer to communicative double contingency rather than to the psychic processes of human beings.

2. Information without understanding

Discourses about Big Data are now ubiquitous but still very intransparent. What is really the point? The practical achievements are amazing: today machine learning systems are able to recognize images never encountered before, carry on conversations about unknown topics, analyze medical data and formulate diagnosis, as well as anticipate the behavior, the reasoning, and also the wishes of users. On the basis of Big Data we can (or will soon be able to) build self-driving cars, translate live online phone calls from one language to another, and use digital assistants that deliver the information we need at any given moment.

As several observers claim (Kitchin 2014), however, at the theoretical level it is not yet clear if and how Big Data is leading to a "computational turn in thought and research" (Boyd and Crawford 2012: 663), changing the very idea of data, information and finally science and knowledge (Wagner-Pacifici et al. 2015). It cannot be just a matter of quantity (data is bigger), unless we can show where and how quantity becomes quality.

The premise is the process of "datification" (Mayer-Schönberger and Cukier 2013: 73ff.), which allows to express more and more phenomena in a quantified format that can be analyzed and processed. Algorithms derive data from the information available in materials on the web (texts, documents, videos, blogs, files of all types), and from the information provided by users: our queries, recommendations, comments, chats. They are also able to extract data from information on information: the metadata that describe content and properties of each document, such as title, creator, subject, description, publisher, contributors, type, format, identifier, source, language and much more. Social media also allow to datify emotional and relational aspects such as feelings, moods and relationships between people; and the Internet of Things can extract data from material elements like physical objects and spatial locations. We have many more data than in previous times. Moreover, and most importantly, algorithms are able to use all these data for a variety of secondary uses largely independent of the intent or the original context for which they were produced[9].

The consequence, according to some observers (first Chris Anderson 2008, in an article that ignited a huge debate) is that scientific reasoning as familiar to us, based on hypotheses to be tested and on the identification of causal links, is becoming obsolete. When you have access to all data and enough computational power to analyze it, hypotheses and explanations are no longer necessary. You just go directly and see the results. These results are not the conclusion of a reasoning, but simply the identification of forms and patterns: the discovery of *correlations* that disclose the meaning and the consequences of a phenomenon, regardless of any theory. This led Chris Anderson to the widely quoted (and widely criticized) statement that "with enough data, the numbers speak for themselves" (Anderson 2008).

According to this approach, when you can access all data about a phenomenon (the statistical universe), there is also no need for sampling and probabilistic procedures. You can process the universe itself (n = all), looking for the patterns computers extract from the ocean of data (Kelly 2008). Statistical procedures are seen as related to our limited computing capacity, which forces us to use simplifications and shortcuts. Now that computing capacity is virtually unlimited, this would be no longer necessary, as well as hypotheses and clever demonstrations. "Correlation supersedes causation" (Anderson 2008). There is no need to know "why" you get a given result, only "what" it is (Mayer-Schönberger and Cukier 2013: 7).

This interpretation is extremely controversial and has been criticized on many aspects: data fundamentalism (Crawford, Miltner & Gray 2014), data feticism (Sharon and Zandbergen 2016), mythology and apophenia (seing patterns where none exists: boyd and Crawford 2014: 668), reductionism (Kitchin 2014), opacity (Pasquale 2015), confusion between correlation and causality (Cowls and Schroeder, 2015; Floridi et al. 2016: 5), hidden bias (Gillespie 2014), and several others. Here, however, I am not interested in taking a position in this debate, but in asking why the hypotheses about a radically new way of making sense of data emerge right now and on what basis. What aspects of the development of digitization suggest today a form of information processing fundamentally different from scientific reasoning and independent from its structures?

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[9] See Cardon 2015 on algorithms working “below” the web.

The protagonists of this alleged revolution are algorithms (Cardon 2015), whose advantage has always been not requiring any "creative" thought in their execution (Davis 1958: xv). In algorithms, and in the digital management of data that relies on them, processing and mapping of data have nothing to do with understanding - indeed, in many cases the claim to understand would be quite an obstacle. The machine has other ways to test the correctness of procedures. In the field of Big Data a certain "messiness" is a positive factor (Mayer-Schönberger and Cukier 2013: 33): imprecision and errors make the working of algorithms more flexible, and are neutralized by the increase in data. When the number of elements to be analyzed grows (up to today's incredible levels of Petabytes and Zettabytes) not only performance does not get worse, but gradually becomes more precise and reliable - but less and less comprehensible (Burrell 2016).

3. Artificial Communication

The communicative relevance of Big Data is a consequence: we are facing a way to process data (and to manage information) that is different from human information processing and understanding - and this is the root of the success of these technologies. Just as men first became able to fly when they abandoned the idea of building machines that flap their wings like birds,[10] digital information processing only managed to achieve the results that we see today when it abandoned the ambition to reproduce in digital form the processes of the human mind. Since they do not try to resemble our consciousness, algorithms become more and more able to act as competent communication partners, responding appropriately to our requests and providing information that no human mind ever developed and that no human mind could reconstruct.[11]

This is evident in practice but not always in the theory. The metaphors used in the field of Big Data still keep a reference to the human mind and its processes. Indeed, the idea

[10] With Hans Blumenberg's metaphor: Blumenberg 1957.
[11] The idea of a progressive autonomy from human performance is not new: all media introduce a form of communication that in some respect becomes autonomous from a direct coordination with human processes: Luhmann 1997: 216ff. In written communication it is not necessary that the partners are present, with press and mass media it is not even required that they know anything about each other or that they ever met. The reader produces his own communication, with a rhythm, a timing and an order that can be quite different from those of the issuer. The information that the receiver gets is more and more independent from what the issuer had in mind. With algorithms, however, apparently it is not even needed that someone ever had that information in mind.

is very widespread that the recent procedures of "deep learning" are so effective because they are based on neural networks reproducing the functioning of the human brain. As most researchers admit (Goodfellow et al. 2016: 15; Wolchover 2014), however, we still know very little about the working of our brain, which makes the analogy quite curious: it can be seen as an orientation to lack of knowledge. If the machines no longer try to understand meanings as the human mind, cannot we find a different, more fitting metaphor?

The recent approach of Big Data is actually very different from the models of Artificial Intelligence (AI) from the 1970s and 1980s, that aimed, by imitation or by analogy ("strong" and "weak” AI) at reproducing with a machine the processes of human intelligence. Now this is no longer what the systems do, and some designers declare it explicitly: "We do not try and copy intelligence" (Solon 2012) – it would be too heavy a burden. Translation programs do not try to understand the documents and their designers do not rely on any theory of language (Boellstorff 2013). Algorithms translate texts from Chinese without knowing Chinese, and the programmers do not know it either. Spell checkers can correct typographical errors in any language because they do not know the languages nor their (always different) spelling rules. Digital assistants operate with words without understanding what words mean and text-producing algorithms "don’t reason like people in order to write like people" (Hammond 2015: 7). Examples can be multiplied from all areas in which algorithms are most successful. Algorithms competing with human players in chess, poker, and Go do not have any knowledge of the games nor of the subleties of human strategies (Silver and Hassabis 2016)[12]. Recommendation programs using collaborative filtering know absolutely nothing about the movies, songs or books they suggest, and can operate as reliable tastemakers (Grossman 2010; Kitchin 2014: 4). Computer-based personality judgments work “automatically and without involving human socio-cognitive skills” (Youyou, Kosinski and Stillwell 2014: 1036).

One could say - and this is the idea that I propose here - that what these programs are reproducing is not intelligence but rather communication. What makes algorithms socially relevant and useful, is their ability to act as partners in a communication that produces and circulates information, independently from their intelligence. Can we say that the web does not realize an Artificial Intelligence but a kind of Artificial Communication,

[12] The programmers of Libratus, the poker AI that defeated the best human players in January 2017, say that “it develops a strategy completely independently from human play, and it can be very different from the way humans play the game” : cf. Metz 2017b.

which provides our society with unforeseen and unpredictable information?[13] Maybe society as a whole becomes "smarter" not because it artificially reproduces intelligence, but because it creates a new form of communication using data in a different way (Esposito 2013).

That the focus of the web is on communication rather than on intelligence is also confirmed by the rampant success of social media, which were not foreseen in any model of its evolution. The web today is led by contacts, links, tweets and likes more than by meaningful connections between contents and between sites (Rogers 2013: 155; Vis 2013) – it is driven by communication, not by human understanding.[14] Every link (every communicative behavior) is treated as a like, and "liking" and "being like" also have been equated (Seaver 2012). Everything that happens in the web becomes a fact and is used as a fact, having consequences and producing information.

4. Communication and thought

If we move from referring to (artificial) consciousness to referring to (artificial) communication[15], however, we must ask different questions. What kind of communication is mediated by the web? Does it still make sense to talk of communication when data processing is performed by a machine, which does not understand the communicated contents? Is it still communication, and with whom? Obviously the answers to these questions depend on the concept of communication, which should be sufficiently precise and powerful to cover also those cases, including them or not.

Here we can see the advantages of Luhmann's theory, and the reason why I think that it is particularly appropriate to deal with the innovative aspects of digital communication. Most theories of communication assume that for communication to come about, the mental processes of the participants must converge on some common content. The partners must share the same thought, or at least part of it, whether they agree or not. Even when theories do not require the identity of information (minus noise) in the sense of Shannon and Weaver and of transmission models, at least they expect some identity of decoding, meaning or interpretation. In the interaction with machines, however, we are

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[13] Braun-Thürmann 2013 describes as "Artificial Interaction" the cases in which technical artifacts are involved. I rather refer to communication, to highlight the relevance of web connection and Big Data.

[14] The very distinction between social facts and personal opinions seem to be fading (Latour 2007).

[15] As proposed also by Malsch and Schlieder 2004, who suggest to develop Communication Oriented Modeling (COM) a an alternative to Agent Oriented Modeling (AOM).

dealing with a situation in which the communication partner is an algorithm that does not understand the content, the meaning nor the interpretations, and works just because of this. The user cannot share any content with his interlocutor, because the interlocutor does not know any content. At issue here is whether communication comes about or not. Is it always an "aberrant" situation[16]? How can one keep some control on the ongoing processes and adequately describe what happens?

When we are dealing with a partner who does not think, the concept of communication of the theory of social systems has the great advantage of not being based on psychic contents and not requiring any sharing of thoughts among the participants. Communication is defined starting from the receiver, not from the issuer, who can get an information different from what the utterer had in mind[17]. According with Luhmann (1984: 193ff.), communication exists not when somebody says something[18], but when somebody realizes that someone else said something. You can write entire books and make elaborate speeches, but if no one reads or listens and if no one even realizes it, it is not plausible to think that communication came about. However, if a receiver understands information that (according to him) someone meant to utter, communication takes place - whatever the information and whatever the issuer had in mind (or did not have in mind). Communication is thus defined as a unit of three selections: information, utterance (*Mitteilung*) and understanding (ibid: 196).[19]

The power and improbability of this notion of communication are related to the fact (which is fundamental for our focus on algorithms) that it does not include the thoughts of the participants, hence in principle could also involve participants who do not think (like algorithms). That communication is not made of thoughts, however, does not mean of course that communication can proceed without the participation of thinking people. If no one listens and no one participates, communication doesn't go on. Communication requires participants who think, nevertheless is not made of their thoughts. Conversely, knowing the thoughts of participants you do not yet know the meaning of communication.

[16] In the sense of semiotics' "aberrant decoding" (Eco and Fabbri 1978).

[17] The advantage has been observed also by Malsch and Schlieder 2004, who propose therefore to substitute the usual "intentional stance" with a "receptional stance".

[18] Or writes, or indicates, or broadcasts - the concept is not bound to oral communication.

[19] Strictly speaking, it should be specified that the understanding included in the definition of communication has a social and not a psychic reference: it does not coincide with what the receiver understands and thinks, but refers to the potential of meaning (Sinn) available to any possible participant in the communication, who can always understand it in a different way: cf. Luhmann 1988; 1997: 73.

The result is the paradox, often difficult to accept, of a "total dependence and total independence" of communication from consciousness, i.e. from the thoughts of participants (Luhmann 2002: 273) [20]. In order for information to enter the communication circuit, an utterance by someone must be understood. Natural phenomena do not produce a communication, if they are not observed and reported by someone. Rock layers are informative for communication only when a geologist that can interpret them speaks about them in class or writes an article (communicates) and someone listens to his communication or reads it. The same applies to bodies (a disease does not communicate, if there isn't someone interpreting and communicating the symptoms) and for machines. In all these cases, one communicates with the utterer, not with the rocks or with the bodies. In this sense, communication is totally dependent on the participation of consciousness, which not only must develop a thought, but also must be motivated to communicate it and to pay attention to what is being said / written (which is not at all obvious). At the same time communication remains independent from individual thoughts, because those who read the article by the geologist don't know his thoughts and can always understand the text in a different way[21]. From your individual perspective and from your background, you can draw from a communication information that the utterer did not have in mind and doesn't know, which however is a result of the communicative event. And someone else can always understand the communication differently. Basically every information is different for every participant, because we each understand it from our idiosyncratic point of view (von Foerster 1970). Nevertheless we communicate – or we communicate precisely because of this.

Even if it is not made of people and of their thoughts, communication as we know it so far (also as distant communication conveyed by technologies like print or television) normally requires the participation of at least two consciousnesses who address their thoughts to it. There must be someone (or several people) who for some reason listens / reads / watches that someone else for some reason utters something (Luhmann 1988). This distinguishes communication from simple perception, possibly also of others and of their behavior. We get a lot of information watching (or otherwise analyzing) objects and living

[20] "Communication happens only through consciousness with the help of consciousness, so never operationally as consciousness": Luhmann 2002: 274.

[21] The theory of social systems speaks of "structural coupling" between communication and consciousness, using a term proposed by Humberto Maturana in biology. Cf. Luhmann 1997: 92ff.

beings, or also the appearance and the behavior of humans; we study plants and stones, machines and bodies, but we do not communicate with them. Communication comes about when the observer not only knows something but also knows that someone is saying (or writing, or somehow conveying) it, i.e. when he not only gets information but also knows that someone wanted to convey it.

This cannot be taken for granted, because everyone can turn his attention wherever he wants, and not every observation is a communication. Since Parsons, sociology speaks of a condition of *double contingency*[22] to indicate the very specific situation in which both the receiver and the issuer, who can always do something else[23], each refer to the contingency of the other. Contingency is double not simply because there are two contingent participants, but because each of them decides what to do (or select) depending on what the other is doing (selecting), and both know it[24]. Double contingency as reflected contingency is the defining condition of any communicative event.

5. Communicating with a partner who does not think

What if one participant is an algorithm that does not think, does not mean, and does not have expectations? What happens to double contingency? If we still want to talk of communication we must include the case in which there is only one person, facing a smart algorithm that can participate in the communication. But in order to be a communication partner this algorithm must operate differently from a machine or a watch, from which we get information but with which we do not communicate. Where is the difference? Are the defining elements of communication still present? Do smart algorithms provide the performance of a communicative partner producing an equivalent of double contingency?

The entire issue of communication with machines and, if you want, what remains of the Turing test (Turing 1950), depend on the answers to these questions. What matters is not whether the person is or is not aware of dealing with a machine, because this now

[22] The term was originally introduced by Parsons (Parsons and Shils 1951: 3-29), and taken up later by Luhmann 1984: 148 ff. Here I refer to Luhmann’s more abstract understanding.

[23] They are contingent in the sense of modal theory. Something is contingent when it is neither impossible nor necessary. It can exist or non exist, or exist otherwise: Esposito 2012.

[24] In its "pure" form, double contingency produces the paradox of circular mutual dependency: "I do what you want if you do what I want" (Luhmann 1984: 166). Who starts? In fact, normally there are structures that orient behavior and solve the paralysis: someone greets, nods, says something.

happens every day and usually is not relevant. Today we all communicate with bots without knowing it (in online service, videogames, social media), and even when we know it, as with personal assistants, normally we do not care[25]. What matters is whether the interaction with the machine has the features of a communication with a contingent autonomous partner. Otherwise it is a form of perception of objects in the environment, which can be extremely complex and informative but has different assumptions and consequences. For example one can be interested in knowing how the machine-object (e.g. a watch) works and for what purposes, but does not get angry with the watch for being late nor cares about understanding what it means[26]. And especially one does not use its indeterminacy to structure one's own, as it happens in communication (a very important point for software programming strategy).

In principle it cannot be excluded that interaction with algorithms is communication, but it must be specified. As we saw above, in systems theory's definition communication is not made of the thoughts of the participants, so theoretically can also include participants who do not communicate, if the recipient thinks they do.[27] It is only required that the unit of information, utterance and understanding is accomplished, i.e. that the recipient understands specific information related to the communicative intention of the counterparty in that event. Not only does the recipient understand an information, he knows (or thinks) that it was uttered by the partner, and that it could be different (contingent). For example, if someone waves his hand to chase away a fly but someone watching him thinks that he wanted to say good-bye, communication comes about, even if the alleged issuer had something else in mind. Or if a reader thinks that the shopping list written by Montale, who only wanted to write a memo and did not intend to communicate anything to anyone, is a poem, interprets and comments it, a communication exists in the world and has consequences, no matter what Montale meant. The thoughts of the utterer are not part of the communication and the receiver cannot access them anyway. If some information related to his behavior is understood and produces further communication (if

[25] A test on WeChat (a popular messaging app in China) on May 29, 2015 with the chatbot xiaoice, showed that people generally don't care that they are chatting with a machine (Wang 2016). In a few weeks, xiaoice had become the 6th most active celebrity on Weibo and had tens of billions of conversations with people, mostly about private matters. The experiment has been considered the largest Turing test in history.

[26] It is not a question of interpretation in the sense of the tradition of hermeneutics, from Schleiermacher onwards. In the words of observation theory, it is no second-order observation (Luhmann 1990).

[27] Someone chooses a behavior that communicates the information. "This can be done intentionally or unintentionally" (Luhmann 1988: 195).

the receiver resumes contact with the person who greeted him or talks with others of their meeting, or if one writes an article about Montale's poem) communication has happened.

Although erroneously, however, these borderline cases involve two human interlocutors, one of which maybe is not thinking about the ongoing communication but still thinks. Different is the case in which the partner to whom the communication is attributed[28] is not a human being, does not operate on the basis of thoughts, and its partner knows it. Can we still speak of communication? How should the machine behave to be a communication partner?

There are precedents. Luhmann routinely communicated with a nonhuman interlocutor, as he claims in the article describing the communication with his much discussed file-card box (*Zettelkasten*: Luhmann 1981). But it was a file-card box built over many decades on the basis of a complex architecture of links and references. For communication to come about, actually, it is not enough that the file-box provides the information that the user registered years before and now cannot remember. When you reflect on your thoughts you do not communicate with yourself, not even if the thoughts are reproduced at a later date (Luhmann 1985). There is no double contingency and no production of specific information in the communication act. But Luhmann's *Zettelkasten* was structured in such a way as to have sufficient complexity to produce authentic surprises and did not simply act as a container (*Behälter*), returning to the author what he formerly put in. The information "produced" in the act of communication was the result of a query (*Anfrage*), which activated the internal network of references, and was different from what had been stored by Luhmann in his notes (Luhmann 1981: 59). Of course the archive is not contingent in the sense of autonomously deciding what to do and not to do, but is perceived by the user as unpredictable, informative and reacting to the specific request of its partner. The answer Luhmann got as a result of his query did not exist before his quest. In such cases there is an added value of communication and then, as Luhmann himself experienced, the

[28] Or "addressed", in the words of Fuchs 1997.

file-card box acts as communication partner[29]. Communication goes on, although no one would think of the archive as a person[30].

In Luhmann's reflection, this form of communication was not particularly problematic[31]. In most cases there are actually two or more people participating in communication, and the reduction to a single individual is the exception. These cases, as those in which the recipient mistakenly attributes to the issuer the intention to communicate, must be rare, because after a certain threshold it would be very difficult to coordinate many such one-sided communications. Exceptions notoriously prove the rule, but they must remain exceptions. Today, however, with a more widespread communication via algorithms, this case seems to occur more often and in a much more complex way. Think about digital personal assistants like Apple's Siri, Amazon's Alexa, Microsoft's Cortana, etc. or about the many cases of conversations with social bots. Through the interaction with algorithms, users get a lot of information, that in many cases did not exist before they formulated their query and is different from what other human beings entered in the sources and in databases. Are these users then communicating with algorithms?

6. Virtual contingency

Algorithms are not human and do not want to be human. But the discriminating factor, as we saw, is not whether the utterer is a person but whether there is double contingency, which so far normally required the participation of two people. The question we must address is not if algorithms are people and not even if they are perceived as people, but if in the interaction with algorithms a condition double of contingency arises, in which each partner is oriented towards the indeterminacy of his counterparty and specific

[29] In this case, however, presumably only for Luhmann. Luhmann file-card box communicates with Luhmann and with nobody else. This does not rule out that others can consult the files for communication purposes, as the long-term project (2015-2030) "Niklas Luhmann - A Passion for Theory. Publishing His Literary Estate and Making It Accessible for Research" at the University of Bielefeld assumes (cf. Schmidt 2017). But these readers communicate with Luhmann through the file-card box, not with the file-card box itself.

[30] What is lacking is evidently motivation. Here the utterance is separated from the intention to communicate. The archive responds to the queries of the questioner, but does not "want" to communicate anything. On the difference between the "classic" concept of communication and a possible new form of communication with algorithms see infra §7.

[31] The article describing it is presented as a kind of joke and partly as a provocation.

information is produced[32]. We must ask whether and how algorithms can become contingent and reflect the contingency of the users, and how this contingency is controlled in the communication process.

Contingency means that there are open possibilities, therefore selection and a certain level of uncertainty. Algorithms by definition do not know uncertainty, because they proceed with no decisions and no creativity, following the instructions that program their behavior. This is their strength and the reason why they can operate efficiently and reliably. Algorithms and traditional machines can be informative, like a watch that tells us something we did not know before (the time), but the information is not uncertain or unpredictable. Different watches all indicate the same time, if they work properly. As von Foerster (1985: 129) observed, if a traditional machine becomes unpredictable we do not think that it is creative or original, we think that it is broken.

The dilemma faced by the designers of smart algorithms, on the contrary, is how to build machines made to be surprising but useful, i.e. how to program and control the production of appropriate and informative surprises. An algorithm that works perfectly (is not broken) produces a contingent outcome. Cozmo, a real-life toy robot based on a series of machine-learning algorithms[33], is "programmed to be unpredictable" (Pierce 2016a), but also to be responsive and fun. Social algoritms do not only provide information but respond appropriately to user requests, producing new and relevant information. The paradoxical purpose of programming intelligent algorithms is to build unpredictable machines in a controlled way. The goal is to control the lack of control (Esposito 1997).

In some cases the contingency of the machine is simply the projection of the contingency of the user. This happens with the robotic toys studied by Sherry Turkle (2011), which function as communication partners because children or elderly people interacting with them project onto them their own contingency. This has always happened with dolls and puppets, with which children play as if the toys understood and responded to their behavior. The performance of robotic toys, which allows them to be more fun than traditional dolls, is not the ability to understand but the ability to "perform understanding" (ibid: 26) in an elaborate and seemingly reactive way. Algorithms allow the machine to react

[32] According to Luhmann, 1997: 304, it is an open question "whether work or play with computers can be conceived as communication; whether for example the feature of double contingency is present *on both sides*. Therefore it also remains an open question whether one should change the concept of communication and how, if one wanted to include this case".

[33] https://anki.com/en-us/cozmo

to the behavior of the user, and this in turn allows the user to project on the machine his own contingency and his meanings, more efficiently than in the interaction with a mute doll (ibid: 39-40)[34]. The toy behaves differently depending on what the user does, making it easier for the user to interpret its behavior as communication. The machine does not give an intelligent answer, it only gives an answer - that becomes intelligent for the user[35].

A surrogate of double contingency is produced, because the user faces his own contingency in an externalized and elaborated form, and interprets it as communication - somehow like Luhmann in his alleged communication with the Zettelkasten. In both cases the interlocutor (the file-card box, the robotic toy) has a sufficiently complex structure for the interaction to produce information different from what the user already knew, and this information is attributed to the partner. The user communicates with the machine even if the machine does not communicate with the user.

Not only children do this, and it does not only happen in the interaction with anthropomorphic or animal-resembling devices, like the robotic seals and dogs studied by Turkle. Various experiments show that people, without realizing it, deal with computers as if they were real people (Nass and Yan 2010). For example they evaluate the work of the computer in more positive terms if the assessment is done on the same computer, as if they did not want to offend it. This dynamics, however, has rather restrictive limits. The user faces the information he already has, and gets the opportunity to observe it from a different perspective. This can produce additional information, if the user is able to grasp it, but he is not really facing a different perspective. One observes his own perspective from another angle, does not observe the perspective of someone else.

The results can be complex and rewarding. Contingency is multiplied, because it can be observed from the outside. The user experiences a kind of "virtualization" of his own contingency, as observed in a mirror that generates a virtual image.[36] The independent object that you see in the mirror does not exist where the image is: you cannot touch, manipulate, modify it. You cannot enter the mirror. The image, however, is not an illusion: if there is nothing to reflect, no virtual image is produced (Esposito 1995). The mirror shows the image of objects that really exist, but not where it seems. It shows them as if they were

[34] This is also true in the case of refined robots like Cozmo. “It’s up to the humans playing with them to provide creativity” (Pierce 2016a).
[35] The basic issue in videogame design, for example, is “creating the illusion of intelligence (…) rather than creating true intelligence” (Dill 2013, p.3-4).
[36] On virtualisation of sense references in cyberspace, see Thiedecke 2013.

somewhere else, thereby making it possible to see them from a different perspective. The observer can see the objects simultaneously from two different points of view, from the front and from the back, and sees things he could not see otherwise. But the objects remain what they are and do not duplicate. Only the perspectives duplicate. The observer notices it when he observes himself in the mirror: he can see how others see him, and this can be very useful and even surprising[37], but the image by itself does not behave surprisingly or unexpected, and especially not independently. The observer interacts with himself, not with another observer.

Something similar occurs with the reflection of contingency in the interaction with robotic toys. Therefore we can speak of virtualization of contingency. The interaction is meaningful because it produces information that did not exist previously, neither for the user nor for the machine. But this contingency is the result of the duplication of the perspective of the user, who observes his own contingency from a different perspective. The observers do not duplicate, what duplicates is the perspective of the same observer. No authentic double contingency is produced as reflected (and unpredictable) contingency between two communicating parties. What is doubled is the contingency of a single observer interacting with himself as if he were someone else. But two times simple contingency is no double contingency. In this interaction the observer can certainly acquire information that he could not get otherwise, can have fun and find company, but does not face the variety and unpredictability of a different perspective, as in communication.

Smart algorithms, however, go further, and do something different and more enigmatic than this kind of robotic toys[38]. When the user interacts with an algorithm capable of learning (maybe unsupervised: Russell and Norvig 2003: 763f.; Etzioni 2016), he is facing a contingency that is not his own - although it does not belong to the machine. He does not observe himself from a different perspective, he faces the perspective of someone else. The machine in this case is not only behaving in such a way as to allow the user to think that it communicates, it actually produces information from a different perspective. The perspective that the machine presents is still a reflected perspective, because the algorithm inevitably does not know any contingency, but is not the perspective of the user. The

[37] And full of consequences, as Narcissus (and Lacan) show.

[38] Obviously robots that utilize forms of machine learning fall into this category.

algorithm reflects and represents the perspective of other observers, and the user observes through the machine a re-elaboration of other users' observation.

7. Googlization

Where does the algorithm find the contingency to reflect? How does it access the external perspectives it elaborates and presents to its users? To be able to act as communication partners, algorithms must be on the web (Hardy 2016). Artificial communication would not be possible without the web, as smart and sophisticated algorithms can be. Actually the issue of communication with algorithms emerged once algorithms were connected to the web. The path-breaking effect of the Web 2.0 (and presumably of the Web 3.0) is not so much customization but rather the inclusion and exploitation of virtual contingency, which parasitically "feeds" on the contributions by the users and uses them actively to increase its own complexity - and also the complexity of communication. Apparently we can communicate with algorithms experiencing an (artificial) form of unpredictability and reflection – or, if you want, of double contingency.

The symbol of this approach is Google, and this is also the reason for its huge success. The breakthrough came in 1998 with the introduction of link analysis after the spread of the www, which existed then for almost 10 years (Langville & Meyer 2006: 4ff.). The former information retrieval was a search in a limited, non-linked and static collection of documents. Organization and categorization of information were entrusted to specialists such as librarians, journal editors, or experts in various fields. Link analysis, instead, is based on the web and introduces a form of information retrieval that becomes huge, dynamic (unlike traditional documents, web pages are constantly changing their content), hyperlinked, but above all self-organized. The structure is decided not by experts but by the dynamics of the web. And it is incomparably more efficient.

It is a radical conceptual turn adopted in the design of the algorithm PageRank in Google, which thus "invented" the Internet as we know it today (Metz 2012). Its authors, and later owners of the company, describe it in a 1999 article (Page at al.)[39] that starts from the idea of exploiting the link structure of the web as a large hypertext system. The key

[39] Interestingly, the third author, with Larry Page and Sergey Brin, is Terry Winograd, who together with Fernando Flores wrote a decade earlier one of the reference texts for a communication-oriented approach to artificial intelligence: cf. Winograd & Flores 1986.

insight was to determine which pages are important and for whom disregarding completely the content of the pages themselves (ibid: 15). To appropriately decide the ranking of pages responding to users' requests, the system uses information that is external to the Web pages and refers rather to what other users did in their previous activity. In other words: to decide which pages are important PageRank does not go and see what they say and how they say it, but looks at how often they were linked to and by whom. PageRank is based on the number of backlinks to the pages (how many times they have been pointed to by other websites) and on their importance, according to the model of scientific referees - where the "importance" of backlinks depends itself on how many links they have. The definition of relevance is openly circular: "a page has high rank if the sum of the ranks of its backlinks is high" (ibid: 3), including both the case of a page with many not particularly authoritative backlinks and that of a page with a few highly linked backlinks.

The genius of PageRank lies in giving up completely understanding what the page says, and relying solely on the structure and the dynamics of communication. Google's creators do not even try to come up with a great organizational scheme for the web based on experienced and competent consultants, as did the competing search engines from Altavista to Yahoo. They do not try to understand and not try to build an algorithm that understands. "Instead, they got everyone else to do it for them" (Grimmelmann 2009: 941), surfing the net and making connections. Contents come into play later, as a result of the classification and not as a premise. Google uses the links to learn not only how important a page is, but also what it is about. If the links to a given page use a certain sentence, the system infers that the sentence accurately describes that page and takes this into account for later searches. The algorithm is designed to apprehend and reflect back the choices made by the users (Gillespie 2014), activating a recursive loop in which the users use the algorithm to get the information, their research modify the algorithm, and the algorithm then impinges on their subsequent searches for information. What the programmers design is only the algorithm's ability to self-modify. What the algorithm selects and how, depends on how the users are using it.

The system has then been developed in order to take into account not only popularity but also other factors such as users click behavior, reading time or patterns of query reformulation (Granka 2010: 367). As Google declares in the InsideSearch pages of its website (https://www.google.com/insidesearch/howsearchworks/), today algorithms rely on more than 200 signals and clues referring to "things like the terms in websites, the freshness of content, your region". The company produced a Knowledge Graph that provides a semantic connection between the various entities and allows for more rapid and appropriate responses, including also information and answers no one had previously thought (Hamburger 2012). The "intelligence" of the system, however, still derives from the use of the previous activity and from the sources of information available on the web, from Wikipedia to databases of common knowledge, to give people what they are looking for even if they do not know it. As John Gianandrea, Director of Engineering at Google, declares: when one is looking for Einstein on Google, "We're not trying to tell you what's important about Einstein - we're trying to tell you about what humanity is looking for when they search". The intelligence of the system is still the intelligence of the users, that the algorithm exploits to direct and organize its behavior.

Google has become the symbol of an approach that can be found in all successful projects on the web. Since 2003 the term "googlization" (Rogers 2013: 83ff.) has been introduced to describe the spread in more and more applications and contexts of a model that does not rely on traditional status makers like editors or experts, but "feeds" on the dynamics of the web to organize its operations and even itself. The web is guided by a "googlization of everything" (Vaidhyanathan 2011) which takes advantage of the operations performed by users to produce a condition in which "Google works for us because it seems to read our minds" (ibid: 51) - but actually does not need it. It only uses the results of our minds to draw directions, and then produces information that none of us had in mind.

Google, and all systems that work in the same way, feeds on the information provided by users to produce other information it introduces into the communication circuit[40]. It is this information that users, if they are able to understand it, get from the interaction with algorithms, and that cannot be attributed to none other than the algorithms. In the communication with algorithms, it does not make sense to refer to the perspective of those who entered the data, because they could not know how the data would be used, and it makes no sense to refer to what the algorithm meant, because it did not mean anything. Constraints and orientation do not depend on intentions but on programs, which are normally inaccessible (Luhmann 2002: 143). The utterance (*Mitteilung*)

[40] Luhmann 1997: 118: “we can regard as likely that computers will allow for other forms of structural coupling”.

selects the information relevant for the ongoing communication, but the criteria that guide this selection by the programs do not serve to orient understanding. The real innovation in the communication with algorithms is that understanding is no longer oriented to the meaning of the utterance[41].

As Sherry Turkle remarks (2011: 55), what you lose talking with a bot or a robot as communication partner is alterity, "the ability to see the world through the eyes of another". Algorithms do not act as Alter Egos, and if you communicate with an algorithm you do not communicate with an Alter Ego. You do not observe how another (like you) observes, you observe through the algorithm what others also can observe in communication[42].

Nevertheless, and maintaining all the differences between interaction with algorithms and interaction with human beings[43], in these cases we could think about a new form of communication. The user receives a contingent response that reacts to his contingency, and not only reflects his indeterminacy. The algorithm makes selections and choices based on criteria that are not random, but that the user does not know and must not know. The algorithm reflects and elaborates the indeterminacy of all participants, and each user faces the contingency of the others, infinitely surprising and informative. It is still virtual contingency, but reflected in a mirror in which everyone sees not himself but the other observers communicating - generating a kind of "virtual double contingency". They do not communicate with him, but the result is the answer to his specific questions and would not exist if he didn't ask them. The success of Google and of the models that adopt the same strategy is due to this: apparently their algorithms communicate with users, and are able to do so precisely because they do not try to understand contents. They do not artificially reproduce intelligence, but directly engage in communication.

8. What algorithms learn

If this is still communication, we are dealing with a form of artificial communication. With artificial here I mean not only that it was produced by someone, because obviously all

[41] "The unity of utterance (*Mitteilung*) and understanding is abandoned": Luhmann 1997: 309 – even if both selections are still required in any communication.
[42] According to Luhmann (2002: 314), "One is first-order observer again".
[43] The result is not a form of "hybridization" (Hayles 2012), because the working of algorithms relies on the ability to process psychic contingency in their own forms, i.e. on the difference and not the mixture of human and digital processes.

communication would be artificial in this sense.[44] With artificial communication I mean communication that involves an entity, the algorithm, which has been built and programmed by someone to act as a communication partner. It is artificial because you communicate with the product of someone without communicating with the person who produced it[45].

What is artificial is the perspective of the partner, that is produced by the algorithm starting from the perspectives of web users. The algorithm uses them to create a different perspective, that becomes the one of the communication partner with which users interact. It succeeds in doing so if it learns to learn by itself, i.e. to develop a practice of unsupervised learning, in which the algorithm does not learns what others teach. It decides autonomously what to learn and what to communicate[46]. Unsupervised learning, however, is predictably rather enigmatic, as the classic communicative paradox of Palo Alto school (Watzlawick, Beavin & Jackson 1962): "be spontaneous", or as all exhortations to be creative. How can you teach creativity, i.e., how can you program learning without knowing what the student-machine has to learn? This is not the classic educational problem of teaching to learn (Luhmann & Schorr 1979: 85), teaching a methodology and not contents. Here not only you don't know what, you don't even know how the algorithm has to learn, because you don't intend to reproduce human capabilities. The power of the algorithm relies in operating differently.

In practice, unsupervised learning is realized as reinforcement learning[47], in which the algorithm works freely and at the end is told which results are satisfactory (Russell and Norvig 2003: 763f.; Etzioni 2016). You do not teach the machine to do things (as in supervised learning). The machine makes random moves, as if it tried to play a game without

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[44] And obviously many communications involve humanly constructed (i.e. artificial) entities (ANT's socio-technical devices: for example Callon 2004), but not as communication partners. Malsch 1997 speaks of Artificial Societies as a provocation.
[45] All social objects are constructed, hence not natural, but this does not mean that using them one communicates. You don't communicate with the maker of a corkscrew when you understand how it works, and you don't communicate with the corkscrew itself (Eco 2012). You can communicate through objects, as in the case of works of art or design, and of course in the case of books - but then you communicate with the author. The object is artificial, not the communication.
[46] The algorithm itself is quite general: it can learn to solve any possible problem, from playing Go to controlling the parameters of a cooling system in order to improve fuel efficiency (Taylor 2016).
[47] Strictly speaking there is a difference, because real unsupervised learning is used when you do not even know what you are looking for and ask the machine to find any configuration, letting " data speak " (Amoore and Piotukh 2015: 351). Actually, however, there are always too many results that fit the data, most of which are irrelevant. One must therefore choose, deciding which results are valuable and will be used (Agrawal 2003; Agrawal at al. 1993). If the operations proceed, the selection itself is a form of reinforcement, of a communicative kind.

knowing the rules, and after a number of attempts you tell it if it won or lost (reinforcement). You do not teach the algorithm the moves and not even the rules, but, as shown by the much-discussed competitions in chess or GO, it can become able to defeat the most qualified champions. The algorithm uses reinforcements to calculate in its own way an evaluation function that indicates which moves to make – without making predictions, without a game strategy, without "thinking" and without imagining the perspective of the counterparty. As the programmers of AlphaGo, the computing system built by Google to play GO, say: "our goal is to beat the best human players, not just to mimic them" (Silver & Hassabis 2016). The machine does not reason like human beings and in its behavior there is nothing to understand[48]. AlphaGo does not plan but calculates and decides while playing what to do depending on the opponent's moves. The programmers themselves do not understand the "reasoning" of the algorithm. When they tell it that it is "wrong", they merely signal that there is an error, without telling what it is and without knowing it.

In the interaction with users, a learning algorithm gathers a lot of reinforcements of this kind from the behavior of people: if they accept the result, if they click, if they go on searching. It then uses them to direct its own behavior, which becomes more and more refined. AlphaGo and other game algorithm learn via self-play, refining their skills with a trial and error process (Schölkopf 2015; Mnih et al. 2015). The system is trained with data from a server that allows people to play against each other on the Internet. The players are all amateurs and the skills acquired are rather coarse, but the program enormously refines them playing millions of games against itself. The system learns "not just from human moves, but from moves generated by multiple versions of itself" (Metz 2016a). In this process of "self-supervised learning" (Etzioni et al. 2006) the algorithm becomes incomparably better than the players from which it learned, who would not be able to understand its moves. It can learn how to win at GO or at videogames and can learn to give satisfactory answers to user requests, but it does not learn anything about the world, about the users or about the issues it deals with. It only learns about itself (Hammond 2015: 27).

The algorithm does not become more informed or more intelligent, it just learns to work better. But thereby it can produce an increasingly complex communication with its users, who can learn unknown things about the world and about themselves.

[48] The features in the high-dimentional space of the algorithm have no human interpretation: they are just the values of the hidden nodes in a network that was trained for a task: Taylor 2016.

Communication becomes more effective, and new information is produced. "A lot of situations where you invoke machine learning, are because you do not really understand what the system should do" (Michael Warner, a robotic CMU researcher, quoted in Pierce 2016a), but you can learn it from the working of the machine itself.

We can learn from communication with algorithms. An example is the already legendary move 37 in the game of March 2016 between Lee Sedol, one of the world's top GO players, and AlphaGo. The move has been described by all observers as absolutely surprising. "It was not a human move" and couldn't have come to the mind of any human being (Metz 2016c). It was actually produced by an algorithm that does not have a mind, but is the move that allowed it to win the game and then the encounter. Looking back later, Go players found the move absolutely beautiful and brilliant, and started from it to rethink their game strategies, dramatically improving them – they started to learn.[49] Following this revision, Lee Sedol himself produced the celebrated highly unlikely (1 in 10,000) move 78 ("The Touch of God") in the 4th game with AlphaGo, the only one he actually won (Metz 2016b; Taylor 2016).

The player defeated the algorithm re-elaborating with human skills a move that no human could devise. It is likely that the algorithm later will also incorporate move 78 in its range of possibilities and will also learn to manage it and its consequences,[50] but it would not have been able to do this without the human intervention that devised it - and in fact lost that game. No algorithm, however high its self-learning ability, can generate possibilities that are not implicit in the data supplied (Etzioni 2016). No algorithm can independently generate contingency, but the contingency that the algorithm processes can also be the result of the interaction of human beings with the algorithm.

9. Conclusion

Even and especially if the algorithm is not an Alter Ego, does not work with a strategy and does not understand its counterpart, in the interaction with machines human users can learn something that no one knew or could have imagined, which changes their way of

[49] Ke Jie, a Chinese grandmaster who met AphaGo in a match in May 2017, explicitly declared that the algorithm changed the way the top masters play the game, making moves that are reminiscent of AlphaGo's own style (Mozur 2017).
[50] AlphaGo actually also won the three-match series against Ke Jie in May 2017.

observing. People learning to learn from machines increases the complexity of communication in general. In the case of Go it was the game strategy, but the same mechanisms are applied in designing other social algorithms.[51]

This is what sociological theory should be able to deal with. Whether one decides that interaction with algorithms is a specific form of communication and that the concept of communication should be amended accordingly, or one decides that algorithms are not communication partners, what matters is to adequately describe the development of digital communication. We must be able to show how the interaction with algorithms affects the communication of society in general (Luhmann 1997: 304) and to provide insights that can help to direct the work of those who program and build algorithms.

In more and more areas, reference to intelligence does not help, whether that be cased in which things are communicating (e.g. the Internet of Things) or cases in which communications are treated as things (e.g. Digital Humanities). The scenario of the Internet of Things (IoT) involves a network that connects machines, people and real world objects interacting with one another as people do in the web today (Höller et al 2014). The idea is that objects could communicate with objects and people in the same way that people communicate with other people, extending enormously the boundaries and forms of possible interactions. At the same time, and conversely, a new form of algorithmic reading seems to be emerging (Hayles 2012, p.46; Sneha 2014; Kirschenbaum 2007), where texts are treated not as communications but as objects.[52] A set of algorithms process enormous amounts of texts differently from what a human reader would do even in the unlikely case that he could read them all, searching for patterns and correlations independently from interpretation (Moretti 2005, p.10).

Does this mean that we are moving towards a state of widespread intelligence where there will be no difference between algorithms and people, between "intelligent" objects and minds involved in communication? My impression, instead, is that these developments require a radical shift of reference from intelligence to communication. What algorithms try to reproduce is not the consciousness of people but the informativity of communication.

[51] "Because the methods we have used are general purpose, our hope is that one day they could be extended to help us address some of society's toughest and most pressing problems": Silver & Hassabis 2016. Actually the techniques developed in AlphaGo are presently used in a multiplicity of applications in which robots interact with humans: Metz 2017a.

[52] That this kind of processing is called reading can be traced back to the debate around the distinction between close reading and distant reading originated by Moretti (2005).

New forms of communication can combine the performances of algorithm with those of people, but not because algorithms are confused with people or because machines become intelligent. The working of algorithms is and becomes increasingly different from that of people, but this difference can give rise to a new way of dealing with data and producing differences in the communication circuit.

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