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Deep Learning in a Hypercomplex Third-order Society

A spiral of paradox and deparadoxication

Abstract

Type: Conceptual

Purpose: Expecting Deep Learning(DL) artificial intelligence widely applied, the epistemology of DL and its consequences is conceptualized.

Design/methodology/approach: Revisiting the notion of third-order observation, blind spots and paradox-deparadoxication, third-order observation is explained regarding hypercomplex understanding and linked with Peirce's concepts: Firstness/Secondness/Thirdness as to bridge a Luhmannian/Peircian understanding of media reproducing Thirds, not only Seconds. This is used for generalizing an epistemology of DL and discussing consequences of blind spots, paradoxes, complexity and challenges of trusting.

Findings: Prediction of DL being part of an endless spiral reducing complexity, by creating even more complexity as a paradox-deparadoxication having no final solution.

Practical implications: A research agenda underlining emergens, consequences of blind spots, challenged confidence and trust/distrust when algorithms are "black-boxed" - besides foreseeable questions regarding emerging new structures and regimes of power/coercion and risks/dangers.

Originality/Value: Adding to the research literature by showing form theoretical distinctions useful when researching DL.

Keywords: Deep Learning techniques, third-order observation, blind spots, paradox-deparadoxication, confidence/trust/distrust.

1. Introduction

The combined availability of powerful computer networks, Big Data and Deep Learning[1] (see later) is bringing the field of Machine Learning[2] to a new level. One could say that the society reaches a point of history, in which it gets the ability to observe itself in a new way. Social systems produce so much data on every operation, and by applying Deep Learning techniques, they gain a new way of becoming aware.

Deep Learning is still in its infancy. Only few Deep Learning projects existed four years ago; now thousands or more projects are ongoing. Some of the main fields are medicine, law, robotics, driving cars, cyber-war, environment and climate research, astronomy, arts and music, games, etc. Soon Deep Learning technology is expected to be applied to every conceivable application. As it is not very hard to learn to program Deep Learning technologies and many universities all over the world are now teaching courses on this subject, a large number of students will soon become able to use these technologies to solve a wide variety of problems that would have been regarded as major research programs a decade ago. As expressed by Omohundro (2015): "*We are in a kind of "Cambrian explosion" of these networks right now. Groups all over the world are experimenting with different sizes, structures, and training techniques and other groups are building hardware to make them more efficient*".

Deep Learning may have wide consequences regarding management and organizational development, not only considering data-driven management and decision-making, finance, marketing and human resource management but also concerning expected major changes in job-structures, needs for competencies, and for sense-making, visions and risk management for the future. This paper, however, stays on a more abstract level, in order

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[1]Deep Learning is based on multi-layered neural networks capable of traning themselves by using Big Data as input

[2] Machine Learning is a subset of AI that includes absruse statistical techniques that enable machines to improve at tasks with experience. The category includes deep learning.

to conceptualize, how Deep Leaning is impacting observations and reduction of complexity. These considerations are fundamental for all applications.

Taking the social system theory developed by Niklas Luhmann (1927-1998) as the point of departure, a widespread use of algorithmic learning may give birth to a hypercomplex society in which the selection of third-order observation for AI is to be crucial. However, several Luhmannian theorists (e.g. Moeller, 2006) are quit skeptical about using the term "third-order observation", as a third-order observation is nothing more than a first-order observation of a second-order observation. Thus third-order observations also have blind spots, as all observations do (Luhmann 2012-13: 89; Luhmann 2002a, Luhmann &Fuchs, 1994).

In the present paper, we argue, that this is exactly the important thing to bear in mind – but also very difficult and crucial to consider when estimating and evaluating the social consequences of Deep Learning technology entering many new applications. We end up predicting Deep Learning to be part of a never ending spiral of reducing complexity, by creating even more complexity. This seems to be part of a paradox-deparadoxication going on forever having no final solution. In the conclusion we point to a research agenda addressing this issue.

The structure of the paper is: section 2 provides a brief history and explanation of Deep Learning. Section 3 digs into recent sociological research literature on algorithms, big data and machine learning in order to investigate themes, considerations, approaches and findings, and to explain the contribution and position of this paper.

Section 4, accounts for our analytical strategy, and section 5 accounts for the Luhmannian notions of first, second and third-order observations as well as paradox and deparadoxication. Our precautions against the limits of the notion of third-order observations are taken, and our understanding of Deep Learning and third-order observations are elaborated.

Section 6 links the Luhmannian system theory with the concepts of Peirce: The Firstness, The Secondness and The thirdness (Peirce, 1992), as these concepts may help relate the concepts of observation to Media Technologies, by terms defined by Wilf (2013).

By this conceptualization section 7 explains how society through Deep Learning and Big Data may become a hypercomplex third-order observing society having just as many or even more blind spots and being even more complex than the present society. We discuss how the blind spots inherited by Deep Learning may generate uncalculated risks and unintended dangers, and how Deep Leaning as a paradox simultaneously reduces complexity and creates even more complexity – generating a need for increasingly advanced Artificical Intelligence as to de-paradoxicate this never ending, spiraling paradox. Section 8 summarizes a conclusion and brings suggestions for further research on Deep Learning, management and organizational development.

The practical implications is a research agenda contributing a better grasp of the societal roots and destinies and organizational consequences of a technological revolution which may best be described as part of the next phase of the internet – the internet 3.0, the semantic web[3].

2. A brief history and explanation of Deep Learning

The field of AI research was founded at a conference on the campus of Dartmouth College in the summer of 1956 (Russell & Norvig 2003), and has since then been a discipline of computer science. AI has developed into a diverse field with machine learning and now Deep Learning as more narrowly defined subfields (Guo et al, 2016). AI for a long while was characterized by a programmer supplying all the intelligence to the system by programming it in as a World Model. However, computated in this way, one could argue, that it is "just a program", and not more intelligent than the programmer. A specific Machine Learning technique called Deep Learning, however, has been taking the AI world by storm, since

[3] The term was coined by Tim Berners-Lee for a web of data that can be processed by machines

Hinton and Salakhutdinov's (2006) famous article "Reducing the Dimensionality of Data with Neural Networks". This article was showing, how a multi-layered neural network could be pre-trained one layer at a time. Later on, it appeared, with Big Data as input for the neural networks, pre-training is indeed not needed anymore.

Deep Learning is based on a different approach than AI in the past. It is a subset of machine learning composed of algorithms that permit software to train itself to perform tasks, like speech and image recognition. This is done by exposing multilayered neural networks to vast amounts of data. So rather than modeling the world, Deep Learning is modeling the mind, and by applying the technique of Deep Learning the field of AI has made more progress the last few years than in the preceeding decades on several key AI problems, including large scale face recognition, intelligent visual surveillance, web-scale image retrieval/classification, massive object recognition, speech recognition, natural language processing and signal processing etc. (Jun *et al,* 2016). A milestone was reached when Google's DeepMind machine, AlphaGo, during the spring 2016 won 4-1 in a 5-game match over the world champion of GO[4], Lee Sedol.

3. Recent sociological research literature on algorithms, big data and machine learning - themes, considerations, approaches and findings. Positioning of this paper.

A broadly investigated theme is how algorithms are shaping "power" (Beer, 2017). Some authors suggests algorithms to be held to account, governed and regulated, as *'algorithms have the capacity to shape social and cultural formations and impact directly on individual lives'* (Beer, 2009, p. 994). Spring (2011) argues that algorithms trap individuals and control their lives. Other authors have made studies showing algorithms reshaping and disrupting existing structures e.g. the financial sector (Pascale, 2015). However, drawing on the tradition

[4] GO has trillions of moves, and it is not possible even for a computer to win by calculating possible moves

of the SCOT, Mager (2012) shows how the 'new spirit of capitalism' (Boltanski & Chiapello 2007) gets inscribed in the fabric of search-algorithms by way of social practices. She elaborates how the 'techno-fundamentalist' ideology gets aligned with the capitalist ideology and exploitation schemes of the 'connexionist world'. For her, algorithms are just a medium for the new spirit of capitalism, not being powerful and agential on their own. Neyland and Möllers (2017) argues, that:

> "the conditions and consequences of algorithmic rules only come into being through the careful plaiting of relatively unstable associations of people, things, processes, documents and resources. From this we can say that power is not primarily social in the sense that algorithms alone create an impact on society, but social in the sense of power being derived through algorithmic associations".

Part of the discussion of power also is the algorithms being described as a "black box" (e.g. Kitchin 2017). Neyland & Möllers, (2017) mention the

> "proprietary interest in keeping algorithms enclosed, the technical difficulties involved in making an algorithm transparent (Slavin, 2011) or the problems involved in removing algorithms from their black boxes (Bucher, 2012)". A specific issue concerning social algorithms is, furthermore, that "looking at the algorithms will not yield much insight, because the interplay of social algorithms and behaviors yields patterns that are fundamentally emergent. These patterns cannot be gleaned from reading code" (Lazer, 2015).

This also counts for Deep Learning algorithms.

Another theme in the literature concerns ethics (Eynon, 2013, Jordan and Mitchell 2015, Lazer 2015). In particular privacy; for what purposes data can be used; who should own and benefit from the data; the inclusiveness versus exclusiveness of having access to Big Data as well as consequences for democracy. Bakshy et al. (2015) focus on the ladder asking whether the curation of news feeds by Facebook undermines the role that Facebook plays as a forum for public deliberation, and Lazer (2015) asks, whether a “filter bubble” emerges from this algorithmic curation process.

A theme also gaining interest is the epistemology of algorithms, and how it relates to philosophy of science (Boyd and Cradford, 2012, Frické 2015, Kitchin 2017). Kitchin (2017) states, that being contingent, ontogenetic and performative in nature, and embedded in wider socio-technical assemblages, algorithms can be conceived in a number of ways – technically, computationally, mathematically, politically, culturally, economically, contextually, materially, philosophically and ethically (Kitchin 2017). Kitchin cites Montfort et al. (2012, p. 3) noting: *‘[c]ode is not purely abstract and mathematical; it has significant social, political, and aesthetic dimensions’.* Kitchin also notes, that whilst programmers might seek to maintain a high degree of mechanical objectivity – being distant, detached and impartial in “how”; ‘algorithm’ is still one element in a broader apparatus which means it can never be understood as a technical, objective, impartial form of knowledge or mode of operation. Beer (2017) suggests that we look at the way that notions of the algorithm are evoked as a part of broader rationalities and ways of seeing the world.

> “Exploring the notion of the algorithm may enable us to see how algorithms also play a part in social ordering processes, both in terms of how the algorithm is used to promote certain visions of calculative objectivity and also in relation to the wider governmentalities that this concept might be used to open up” (Beer, 2017).

To position this paper in regard to the research literature, many of these themes may be addressed by a Luhmannian social system theory as well. Both power, semantics as well as how functional differentiated systems may frame algorithms and vice versa will be Luhmannian system theoretical topics (Luhmann1979, 1995, 2012-13). The selected perspective in this paper is linked to the epistemological theme, - but through that, also to the other themes. We will argue, that algorithms push human observers one step aside and let them observe, what is already algorithmically observed, abstracted and algorithmically manipulated utterances, while the algorithm itself is “black boxed”. That leaves the human observer with a first-order and second-order observation *of the algorithmic observations and utterances*. The human observer may gain confidence in the algorithms and select either trust or distrust as a way of reducing complexity in order to act in the algorithmic society. This selection is based on expectations based on the human observer’s mental model of “what is behind” the algorithmic observations, selections and utterances, and whether the risk of trusting the algorithms is worth the risk by increasing the human observer’s “benefits” (Luhmann, 1979). Such a mental model of “what is behind” the algorithms relies on observing that “the machines” observe something under some conditions / in a certain way. This is a third-order observation.

If many human observers trust algorithms, they may gain power, as according to Luhmann (1969, 1979, 1990) may not be a bad thing. Power may also *em*power. A Luhmannian approach, however, distinguish power/coesion, as power dependent on the freedom of agents. A very interesting aspect of coercion is, that coercion can only be exercised at a specific cost:

> “The person exercising coercion must himself take over the burden of selection and decision to the same degree as coercion is being exercised ... the reduction of complexity is not distributed but is transferred to the person using coercion” (Luhmann, 1979: 112).

In this case “the person” has to be understood as “the algorithm”.

Both Borch (2005), Andersen (2009), and Tække (2009) have argued that power (as opposed to coercion) is a condition for more complex systems, which leaves an important question concerning the power theme in the research literature on algorithms: when are algorithms shaping “power”, and when do they apply “coercion”? And WHEN they are applying “coercion” THEN what are the dangers? And WHEN they are applying “power” THEN what are the risks?

Luhmann conceptualizes the notion of risk as opposed to danger – not to security. This reconcptualization was based on the “second-order” level of observation (Luhmann 1993: 21). Distinguishing between risk/danger (Luhmann 1993), risk is a possible damage or loss attributed to a decision, while if the possible damage or loss has been caused externally; then it is a danger, not a risk (Luhmann 1993, 21-2). To the extend Deep Learning algorithms end up making decisions, which is out of human control, they are posing a danger. However, the organization deciding to put Deep Learning in place are running a risk, and the persons trusting the algorithms also run a risk.

The danger imposed by Deep Learning may be job-losses for many people, losses related to a reinforced inequality and social inclusion/exclusion, but also unforeseen, emergent machine decisions out of human control. These emergent phenomena may give birth to the question, whether Deep Learning is reducing or increasing complexity[5] – or if it is a paradox, then what does this implies?

These considerations are to be addressed throughout the rest of this paper.

4. Analytical strategy

This paper is a theoretical and conceptual paper. Our analytical strategy takes its point of departure in a revisiting of the Luhmannian notion of third-order observation, which

[5] Luhmann unfolds his notion of complexity in Luhman (2012:77-83). It is a notion needing that many pages to be explained, and hence the author of this paper want to refer to this description in its full length. However, complexity is in itself a paradox described as “*the unity of a manifold*” (p.78). – And as complexity presupposes itself, it is autologial (p.78). In short: the more elements a unity has and the more it interconnects these elements through relations, the more complex it is (p.79). However, “*highly evolved systems have drastically to limit the connectivity of their elements and must therefore invent something to compensate the concomitant losses in interrelations*” (p79). It is this selective organization, which constitutes a system’s autopoiesis. (And the reason of the increasing differentiation, and the emergence of functions systems in modern societies – see Roth(2015)) “*A system can describe itself as complex in various ways caused by the paradoxical nature of the concept, but also* [because] *an observer can describe the complexity descriptions of another observer so that hypercomplex systems can come into being*,[containing] *a multiplicity of complexity descriptions*”(p.80).

Qvortrup (2003) has thoroughly described. Many luhmannian theorists are critical towards using the notion of third-order observations, as a third-order observation is nothing but a first-order observation applied on a second-order observation – in this way it is not anything special. However, our point of view is that when Deep Learning takes place, observation of the *principles* of machine observations are crucial. Our method of revisiting the concept is through an abductive analysis of what Deep Learning is by applying the conceptualization done by Keiding (2007) in her paper: "Simple, complex and hypercomplex understanding - enhanced sensitivity in observation of information". Before doing so, however, we revisit the fundamental paradox of knowledge as to be produced while having no direct access to the environment. We link these considerations with the way Deep Learning works. Hereafter, we link the Luhmannian system theory with the concepts of Peirce (1992): The Firstness, The Secondness and The thirdness. The reason why we are interested in linking Luhmanns concepts of observation and reflection with Peirce' semiosis is to bridge the study done by Wilf (2013) in which he conceptualizes Media Technologies that Reproduce Seconds versus Media Technologies That Reproduce Thirds. This shows a close relationship to Keiding's concept of hypercomplex understanding. By doing so, Wilf's study (2013) allows us to conceptualize Deep Learning by first investigating how it is applied in Music (studied by Wilf (2013)), and then draw analogies for other fields of application.

The interlinking of Luhmann's social system theory with the semiosis described by Peirce (1992) is nothing new. Authors such as Brier (2003), Dinesen (2013) and Pires (2013) have done this before, however in different ways. In this paper the aim is only to explain the relationship between the social system theory and the conceptual universe produced by Peirce (1992) to such a degree that the analysis conducted by Wilf (2013) makes sense as seen from a luhmannian universe.

Against this backdrop, now having a good conceptual grasp of Deep Learning, we address the issue of using confidence to select trust/distrust. Confidence may be challenged as Deep Learning seems to both decrease complexity and at the same time generate even more complexity in a never ending spiral of paradox-deparadoxication – just like the system of science need to continuously produce even more knowledge in order to resolve or de-paradoxicate the paradox as not having access to the environment of with it produces knowledge (González-Díaz, 2004).

5. The Luhmannian notion of third-order observation, paradox and deparadoxication

To understand Deep Learning as part of an operation of observation, we will below account for the luhmannian conceptualization of first, second and third-order observations.

Luhmann builds his social systems theory on the cybernetics described by Foerster (1984), and on the form theory described by Spencer-Brown (1969). According to the form theory, an observation is an indication within the scope of a distinction (Spencer-Brown 1969). A distinction has two sides, the marked inner side and the unmarked outer side (Andersen, 2001). Any observation has a blind spot. Luhmann also calls that "the excluded middle": "*The unity of the form is not its "higher" intellectual meaning. It is rather the excluded middle, that cannot be observed as long as we observe with the aid of the form*" (Luhmann, 2012, 29). The reason is, that "*every distinction presupposes itself and thus excludes itself from what it can distinguish*" (Luhmann 1990b, 526). The observer is not distinct from the distinction.

Luhmann describes observing from the stance of a first-order observation, as consisting of a ***differentiation of the system itself and the outside world by means of a difference***.

He explains: "*distinctions…as deriving from directives to draw them, because if we did not, we would be unable to indicate anything. We would have nothing to observe and hence* *nothing to pursue*" (Luhmann 2012, 28-29). Thus, first-order observations are concentrating on the systems own autopoietic functions.

Luhmann makes clear, that any second-order observation is always already a first-order observation with a blind spot of its own, in the sense that it draws a distinction and mark one, and not the other side.

> "But second-order observations are indeed not only first-order observation. It is both more and less. It is less because it observes *only* observers and nothing else. It is more because it not only sees (=distinguishes) its object [the observer] but also sees what the object sees and sees **how it sees what it sees, and perhaps even sees what it does not see**. On the level of second-order observation, one can thus see everything: what the observed observer sees, and what the observed observer does not see. […]Only one thing is necessarily excluded: the observation that is actualized in the very moment of observing, it's functioning as a first-order observation". (Luhmann 2002b:114-115).

Luhmann does not pay must attention to third-order observations. However, third-order observation is observing that "someone" observes something ***under some conditions / in a certain way***. This particular observation order has become detached from observations of specific phenomena ("qualia") and is now ***observing "circumstances" of these observations***. In this sense, third-order observations are also observations of observations, just like second-order observations, however, a specific way of observing observations. (On Luhmann and third-order observations, see e.g. Roberts, 1999, Qvortrup, 2003, Keiding, 2007, Schumacher, 2011, Luhmann, N. 2000:61, Moeller 2006)

It is worth noting Moeller (2006) underlining the limitations of third-order observations:

> " No higher-order observations - not even a third-order observation – can observe more "essentially" than a lower-order observation. A third-order observation is still an observation of an observation and thus noting more than a second-order observation. There

is no Platonic climb towards higher and higher realitics – no observation brings us closer to the single light of truth", (Moeller, 2006).

We agree on this limitation of third-order observations and underline, that all observations are having blind spots (Luhmann 2012-13). Noting this, algorithmic learning also cannot move across this line – they are also bound to have blind spots, and will be used by systems observing while having a blind spot, and when certain risks (1993) are calculated others may be due to observer's blind spots.

Having noticed this, we will draw the attention to the paradox pointed out by Spencer-Brown (1969): the impossibility of cognition or knowledge of the world (because of the operational closure of the system), at the same time, as it is absolutely necessary for structural coupling with the environment. This is also why, all autopoietic, self-referential systems are, according to Luhmann, inherently paradoxical. For him, a paradox is a problem which the system *must* solve in order to continue its autopoiesis, and the most effective way to handle a paradox (which Luhmann calls deparadoxication) is by making use of time and moving to a higher level of observation. As expressed by González-Díaz(2004):

> "We can say that we deal with this impossibility of access to our environment by constructing an image of the world and then by developing increasingly sophisticated theories, methods, procedures, and technologies to be able to submit observations to the code of truth".

Keiding (2007) contributes by establishing three forms of understanding: Simple, complex and hypercomplex, which is linked to first, second and third-order observations. Simple understanding (Verstehen in stark vereinfachter Form)(Systeme verstehen Systeme 1986:96) is knowedge produced from first-order observations based on accomplishing each single unit of communication. It implies understanding of the utterance not 'the other'.

Complex understanding is knowledge produced by observing “how” – that is by which distinction – the observer observes. Thus, it is produced by observing the observer. It can be described as “... Handhabung fremder Selbstreferenz” (Systeme verstehen Systeme; Luhmann 1986:96).

The hypercomplex understanding takes into account the observation and construction of hypothetic differences for the conditioning of the single units of the communication. The notion of conditioning, here refers to that in most systems the single events do not only appear as organized through relations, but also the relations appear as organized. Conditioning, thus, refers to “the relationship of relations” – the difference(s), that are framing other differences. Hereby conditioning is delimiting the numbers of potential relations and is reducing the complexity – as does the structures. The hypercomplex understanding may according to Keiding be constructed when an observer is wishing to gain insight into the conditions underpinning the communication regarding which differences are determining the potentialities of meaning within which the actual meaning is decided. This may be regarded as one more layer of abstraction – questioning what is “behind” the “how”.

The form of hypercomplex understanding contributed by Keiding (2007) is illustrated in figure 1.

Figure 1 about here.

The three forms of understanding: Simple, complex and hypercomplex, as accounted for by Keiding (2007) is similar to the communication model described by Qvortrup (2003) developed taking into consideration the communication theory as it was described in Luhmann (1991). All three forms of understanding (which is also referred to as first, second and third-order) may be selected simultaneously in communication.

As seen from the form and the above example, categorizing, conceptualizing and deducing and creating abstract knowledge very much belong to hypercomplex understanding and include third-order observations. However, as described below – and as exemplified and further discussed in section 6, this is also the way in which Deep Learning works – by abstracting from lower-order observations.

Deep Learning, as is the subject of this paper, is called "deep" and is a class of methods and techniques that employ artificial neural networks with multiple layers of increasingly richer functionality. It works so that the lowest layer takes the raw data like images, text, sound, etc. and then each neuron[6] stores some information about the data they encounter. Each neuron in the layer sends information up to the next layers of neurons which learn a more abstract version of the data below it. So the higher up, the more abstract features are learned. Deep Learning algorithms require massive data for feeding into the models. The bottleneck remains in cleaning and processing these data into a required format for powering the machine learning models. However, as more and more big data will be made available for public consumption these are obvious inputs for Deep Learning (Tyagi, 2016).

Keiding's analysis gives us the understanding, that algorithmic learning may provide us with the ability to handle and extract increasingly abstract knowledge, however, for our analysis, the Luhmannian theory of third-order observations, also means that any third-order observations generating hypercomplex understanding, whether performed by machines, humans or other systems, still have blind spots, and cannot prevent unintended dangers or risks in decision-making.

6. The Firstness, the Secondness, the Thirdness… and Media Technologies that Reproduce Seconds versus Thirds.

In this section we will dig deeper into an example of Deep Learning abstraction in order to explain how hypercomplex understanding comes about, and why it makes a difference as compared to complex understanding. In section 7 we will compare this example to other

[6] The neural networks used in Deep Leaning concist of something called artificial neurons

Deep Learning applications, and discuss how this way of observing and generating abstract understanding may evolve in the future and potentially generate even more complexity.

The example builds on an analysis by Wilf (2013) of Media Technologies that Reproduce Seconds versus Media Technologies that Reproduce Thirds. As this analysis builds on Peirce's universe, we need to explain the relationship between the social system theory and the Firstness, the Secondness and the Thirdness (Peirce, 1992). This has been done before by others (Brier, 2003; Dinesen, 2013; Pires 2013), but in different ways. It turns out, that the relationship between Peirce's universe and the social system theory may help the understanding of this abstraction.

Before getting back to the conceptualization, we will briefly explain the case Wilf (2013) takes as the point of departure.

It concerns a

> "fieldwork in a lab at a major institute of technology in the United States, in which computer scientists were in the process of developing a humanoid robot marimba player that, thanks to computerized algorithms, can abstract and enact the styles of different past jazz masters. As part of its training, these algorithms perform statistical analysis on databases that consist of files of different masters' past recorded solos. In actual playing sessions, these algorithms instruct the robot, which I call Syrus, what to play based on this analysis… the fact that they [the algoritms] integrate stochastic processes into their logic …[means]…that their output is seldom repetitious and predictable."(Wilf, 2013: 193-94).

Based on Everaert-Desmedt (2011) one may explain **Firstness** as:

> "a conception of being that is independent of anything else. A quality is a pure, latent potentiality. Firstness belongs to the realm of possibility; it is experienced within a kind of timelessness. Firstness corresponds to emotional experience" (Everaert-Desmedt,, 2011).

We will in this paper correlate **Firstness** to Luhmanns notion of "possible".

Secondness is the mode of being

"that is in relation to something else. This is the category that includes the individual, experience, fact, existence, and action-reaction. Secondness operates within discontinuous time: a certain event occurred at a certain moment, before some other event, which was its consequence. Secondness corresponds to practical experience" (Everaert-Desmedt, 2011).

We will in this paper correlate **Secondness** to Luhmanns notion of "actualized".

Seen in this way we get a form almost similar to the form of meaning (see figure 2), which is repeated in the marked side of the form of hypercomplex understanding as contributed by Keiding (2007), see also in figure 1.

Figure 2 about here.

Thirdness is according to Everaert-Desmedt (2011):

"the mediator through which a first and a second are brought into relation. Thirdness belongs to the domain of rules and laws; however, a law can only be manifested through the occurrences of its application, that is, by secondness; and these occurrences themselves actualize qualities, and therefore, firstness. Whereas secondness is a category of individuality, thirdness and firstness are categories of generality; but the generality of firstness is on the level of possibility, and the generality of thirdness is on the level of necessity, and therefore, prediction. Thirdness is the category of thought, language, representation, and the process of semiosis; it makes social communication possible. Thirdness corresponds to intellectual experience".

It is not easy to correlate Peirce's notion of Thirdness with the luhmannian universe. However, a suggestion is contributed by Pires (2013) describing the Thirdness as what Peirce also express as the "interpretant":

> "More generally, the description of the function of the interpretants in the fixation of meaning represents the semiotic understanding of self-reference, the formation of the internal environment of the system and the individuation of borders through semiotic processes. Processes or events can be of physical, biological, psychic or of communicative nature, varying with the system of reference and the mobilized sign-types and sign-paths".

Wilf explains, that Peirce did not mean that a Third can only be an ad hoc explanation or theory that brings into relation already existing cases but also a principle of generativity; "habit" responsible for generating future events that bear the stamp of this principle, habit, and fact. He regards "Style" as an example of a Third in precisely this respect. That is, it is a regulative principle that can be abstracted from distinct cases and used to predict future ones (Wilf, 2013: 188).

In this way, we get exactly, the abstracted hypercomplex understanding generated by a systems reflexion on the distinction of the system and the environment. Hence, this conceptualization is very close to the notion explained by Keiding (2007).

Wilf (2013) reaches the conclusion, that what distinguishes features of technologies that reproduce Thirds [thirdness], from technologies that reproduce Seconds [secondness], are their ability to synthesize or abstract a disposition or style from discrete cases or Seconds and to enact this disposition and thereby produce new Seconds "in the same style." (Wilf, 2013: 195). Corresponding to a lumannian way of expressing this, it might according to Pires (2013) be for the technology to uncover and reproduce a systems semiotic understanding of self-reference.

For the case Wilf (2013) describes:

> "The computerized algorithms that animate Syrus's playing are not fixed rules that stipulate what specific phrases should be played in a given harmonic situation. Rather, they generate musical content based on probability functions and chance decisions in accordance with the frequencies detected in the jazz masters' solos when subjected to a statistical analysis. Hence, although they are not repetitious, they do reveal a trend, a propensity, or a pattern—in short, a style—over time". (Wilf, 2013: 195)

To be more precise Wilf's definition of Media the reproduce Seconds is:

> "All that a technology that reproduces isolated texts of the same artist, or Seconds, can do with respect to style is to provide users with raw material from which users would need to abstract a style. In other words, it is the user who synthesizes or abstracts a certain style from the isolated texts reproduced by a technology that mediates Seconds" (Wilf, 2013: 195).

Whereas the definition of Media that reproduces Thirds is:

> "In contrast, a technology that reproduces Thirds or a style or a habit or a disposition is a technology that itself performs such an abstraction of a Third from a given corpus of Seconds and is thereby able to enact this Third and indefinitely generate new and novel instantiations of such a style. To abstract and enact Thirds is precisely the role performed by the algorithms that animate" (Wilf, 2013: 196).

The important thing to note is, that this distinction not only regards the algorithmic ability to observe, abstract and generate (not replicate), but it also put aside the user as an observer that now observes already algorithmically observed, abstracted and algorithmically manipulated utterances. However, the algorithm itself is not uttered for the user (it is a black box). The user now only observes the algorithmically manipulated utterances, knowing that they are generated by this "black box". According to Qvortrup (2003) this is a situation of communication in which the institutional conditions for the “sender” are “black boxed” for the “receiver”.

As the luhmannian theory of trust builds on confidence (Luhmann, 1979), which depends on an inner representation of the environment – a lack of such an inner representation may challenges the process of trusting.

For users to learn to co-work with or to perceive such Media that reproduces Thirds, it requires a new competency in understanding (at a general level) how the algorithms work and to evaluate their qualities creatively to make them useful as seen from the user’s own systemic perspective, and therefore selecting to trust the algorithms. That is competencies in generating hypercomplex understanding based on third-order observations as well as in translation through structural coupling.

A sub-conclusion is, that Deep Learning builds abstracted meaning (or understanding), as described by Keiding’s (2007) notion of hypercomplex understanding. However, for the human observer to trust this abstraction, the human observer needs the ability to create an own inner representation of the abstracting system as to select trust or distrust.

7. Deep learning a young field: hypercomplex understanding, uncalculated risks and unintended dangers - Deep Learning as a way of reducing complexity – or a paradox?

The music case that we have conceptualized above is just one area of application for Deep Learning and Media reproducing Thirds. Computerized algorithms that simulate or anticipate style has been used by commercial companies to statistically predict online users’ individual preferences, tastes, and distastes (their style) based on their online behavior (Cheney-Lippold 2011; Seaver 2012). This has been used for various purposes to generate relevant search results, come up with effective advertisement strategies, and be a personal online assistant (e.g. Apple’s Siri). However, many more and increasingly sophisticated applications may appear. One common experience is that many current advertisements are based on online behaviors that are not relevant anymore, as they are based on big data from the past. This may be due to the Deep Learning networks not being generative of content in a user's style - it has not yet become an author who "speaks" on behalf of the user (Goffman, 1981). This is a distinction of reproduction or coproduction of Thirds (Wilf, 2013).

However, in the near future many employees will be going to cowork with Deep Learning technologies, whether it is doctors, nurses, laywers, university scholars, genomic analysts, drivers, market analysts, managers, human resource experts etc. So what may, the above case analysis bring forward as learning points?

According to a luhmannian approach confidence creates expectations that are crucial in selecting trust or distrust to reduce complexity, - also when acting in the algorithmic society (Luhmann 1979). In that way, it is not so surprising that Wilf comes to the conclusion: "*Key to the presumed success of technologies that reproduce Thirds, then, is the training of users to performatively bring about the desired effects that are presented as the achievement of the technology itself"* (Wilf, 2013).

However, even as this training is achieved, and users may apply trust in more and more applications of Deep Learning, still blind spots exist, and may create uncalculated risks and unintended dangers for others. This we will investigate below.

Many consequences may be foreseeable, e.g. massive losses of middle class jobs (World Economic Forum, 2016) and increasing inequality (Schwab, 2016) on the negative side, and as a consequence, also the need of new competences (World Economic Forum, 2016). On the positive side, an increased productivity (Brynjolfsson, & McAfee , 2014; Manyika et al, 2011, Rifkin, 2014, Noronha et al, 2014), among other things caused by the deep learning applied to the Internet-of-Things (Guo et al, 2012, Noronha et al, 2014)**,** smart cities (Guo et al, 2012) and smart grids (Mocanu, 2017), environmental and climate issues (Hemsoth, 2016), as well as to better medical treatments and health care (Chandan et al, 2015). Also cognitive computing aims at reducing the time needed for a person to become an expert (Kelly, 2015), and to use smart cities as learning spaces (Williams, 2017).

However, also the blind spots may create unforeseeable consequences, and that is what we are going to address below.

Classical machine-learning system involved a single program running on a single machine, but as described by Jordan and Mitchell (2015), this is about to change:

> **"…**machine-learning systems are increasingly taking the form of complex collections of software that run on large-scale parallel and distributed computing platforms and provide a range of algorithms and services to data analysts….The word " environment " … refers to the source of the data, which ranges from a set of people who may have privacy or ownership concerns, to the analyst or decision-maker who may have certain requirements on a machine-learning system (for example, that its output be visualizable), and to the social, legal, or political framework surrounding the deployment of a system…The environment also may include other machine-learning systems or other agents, and the overall collection of systems may be cooperative or adversaria" (Jordan and Mitchell, 2015).

As the complexity of the machine-learning systems increases, machine-learning researchers try to formalizing the relationships of resources, aiming to design algorithms that are provably effective in various environments and explicitly allow users to express and control trade-offs among resources (Jordan and Mitchell, 2015). However, to control these trade-offs is exactly what the luhmannian theory of observation predicts as being impossible because blind spots are unavoidable. This is thus one of the alerts for future research.

Deep Learning is a young field, just starting an incredible fast development – yet, still the learning algorithms are targeting single issues. However, according to Jordan and Mitchell (2015), some researchers are now

> "exploring the question of how to construct computer lifelong or never-ending learners that operate nonstop for years, learning thousands of interrelated skills or functions within an overall architecture that allows the system to improve its ability to learn one skill based on having learned another" (Jordan and Mitchell, 2015).

This also means much more complexity build into the algorithmic environments, and in such much more complex systems, emergence takes place (Goldstein, 2011) according to complexity theory. When emergence shows to become usual in these very complex systems, human confidence may get challenged when used as a foundation for prediction and selection of trust/distrust. This is another alert for future research: How may human build trust or distrust under these circumstances?

Another aspect is that whereas current machine-learning systems typically operate in isolation, people often work in teams to collect and analyze data. New machine-learning methods may be capable of working collaboratively with humans to jointly analyze complex data sets, using humans to draw on diverse background knowledge to generate plausible explanations and suggest new hypotheses, and we may see new models of interacting machine learning, organizations as well as biological systems (Jordan and Mitchell, 2015).

This collaboration of man-machine (and nature) may be one of the greatest promises – and of great interest for management and organization studies, but also one that pushes the demands on human competencies in judging the Deep Learning algorithms. How can we trust the algorithms? How can we test their results and consequences in large scale without running risks that are much larger than our ability to calculate? And how can we prepare for the dangers? This is a third alert for future research.

In the beginning of this paper, Deep Learning was presented as a possible way of reducing complexity by getting tools for more and better abstraction. Tools, that allows for abstracting a style – a Thirdness, based on a Secondness. Tools, which may become authors "speaking" on behalf of the user (Goffman, 1981). Deep Learning has also been presented as a tool for increasing productivity and to enhance the ability of levering medicine, environmental and climate knowledge, and much more.

However, as is also stated, Deep Learning also seems to possibly create even more complexity, as more and more complex Deep Learning systems may create emergent phenomena. Human confidence may not be able to predict such emergence and selection of trust as a way of reducing complexity may be challenged.

As a paradox, Deep Learning seems to simultaneously decrease complexity and create even more complexity – and it may end up as a spiral as more and more complex Deep Learning tools may be a strategy to deparadoxication of the ever existing and unavoidable paradox of knowledge, that are produced having no access to the external environment. In this way Deep Learning tools are subject to the same paradox as science, and every production of knowledge As also described by González-Díaz (2004):

> "..our knowledge and science have no way of anticipating each and every next event. Unanticipated, contingent irritations can always appear that can force new structural couplings. In the case of science, this requires the production of new knowledge. For that reason, paradox will be present as long as our knowledge system exists, and so will the need to resolve paradox by the system that Luhmann calls deparadoxication".

Our point is that this is exactly, what also is the case for the development of Deep Learning tools for knowledge production: a never ending spiral of paradox-deparadoxication.

8. Conclusion and suggestions for further research

In section 3 we detected it as being important for the power theme in the research literature on algorithms to differentiate between, when algorithms are shaping "power" and when they are applying "coercion", asking what are the dangers, when they are applying "coersion" and what are the risks, when they are applying "power".

We found, that one coercion caused by algorithms is, that they not only observe, abstract and generate, but also put aside the user as an observer that now observes already algorithmically observed, abstracted and algorithmically manipulated utterances in which the algorithm itself is not uttered for the user (it is a black box). This is a situation of communication in which the institutional conditions for the "sender" are "black boxed" for the "receiver". This may challenge the human observer's building of inner representations.

As the luhmannian theory of trust builds on confidence (Luhmann, 1979), which depends on an inner representation of the environment – a lack of such an inner representation may challenge the process of trusting, and at least need a learning process for human "coworkers" in order to harvest the benefits of Deep Learning. This we point to as an important issue for a research agenda, - also within the field of management and organization.

We also found, that Deep Learning and Big Data seem to drive an opportunity for radical changes of the economy, organizations as well as the society in its entirety. In many cases, these will foster transformative rather than incremental changes in business and operational processes. Structures of the labor markets, the need for competencies, the notion of work, as well as the notion of management and leadership may change as a consequence. These new structures may generate a new regime of power and empowerment, but also coercion creating dangers imposed by Deep Learning as job-losses for many people, losses related to a reinforced inequality and social inclusion/exclusion, but also unforeseen, emergent machine decisions out of human control. This gave birth to the question, whether Deep Learning is reducing or increasing complexity – or if it is a paradox, then what does this implies?

We have found, that a spiraling paradox-deparadoxication takes place implying, that Deep Learning is evolving into more and more profound and complex, integrated and interdependent algorithmic learning systems, which give birth for three aspects of a research agenda:

1) Driven by the ever increasing complexity of deep learning systems, research is needed to address the unavoidable blind spots challenging the idea of designing algorithms that are provably effective in various environments allowing users to express and control trade-offs.

2) As more complexity is build into the Deep Learning environments, emergent phenomena may show to become usual in these very complex systems. Research is needed in how humans build trust or distrust under these circumstances. Human confidence may not be able to predict such emergence and selection of trust/distrust as a way of reducing complexity may be challenged.

3) The collaboration of man-machine (and nature) may be one of the greatest promises – but also one that pushes the demands on human competencies in judging the Deep Learning algorithms. Research is needed in how we can trust the algorithms. How can coworkers test the algorithmic results and consequences in large scale without running risks that are much larger than our ability to calculate? How can we prepare for the dangers? And how can we organize and lead such processes?

As to sum up, research is needed to focus on the emergent effects as well as the side effects of deep learning arising caused by blind sports, which are unavoidable using algorithmic observations. In particular it is needed to address the issue of how to select trust/distrust, when confidence is challenged.

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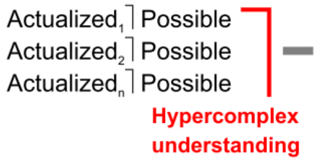
Figure 1. The form of hypercomplex understanding (meaning) as contributed by Keiding (2007)



And an example is given as:

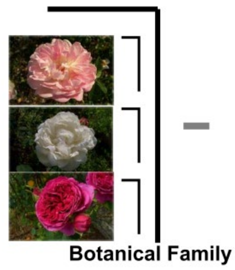


Figure 2. A comparison (as suggested in this paper) of how the difference of the Peircian notions of Secondness and Firstness relate to the Form of meaning.