CHAPTER 12

Algorithmic Logic in Digital Capitalism

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Introduction

In recent years research in social sciences and related academic fields has attributed increased importance to algorithms and their impact on social relations and our everyday lives. While algorithms are nothing particularly new and can be closely related to computing or even mathematics as such, debates have slowly but surely moved beyond the narrow confines of the so-called hard sciences. They are now taking centre stage when authors analyse topics such as political communication, electoral campaigning and mass micro-targeting of potential voters (Moore 2018; Vaidhyanathan 2018), automated trading in stock markets and various other types of financial transactions (Pasquale 2015, Ch. 4; MacKenzie 2017; 2018), or the impact of technological innovations on journalism (Diakopoulos 2019). Their influence is emphasised in healthcare, loan approvals, transportation, traffic-control, city urbanization, education, employment, policing, security and even military conflicts (Fisher 2020; Bridle 2018; Moore 2018; Munn 2018; Mosco 2014). Critical analysis has demonstrated their impact in constructing 'digital poorhouses', since they have become prominent in state administration and eligibility systems for poverty management (Eubanks 2017). It is also impossible to ignore them when considering technologies forming the Internet of Things and cloud computing (Bunz 2014; Mosco 2014), search engines, digital social networking platforms and various recommendation systems, or ranking, reputation and personalisation

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tools aimed at tracking and controlling of behavioural patterns (Mager 2012; Gillespie 2014; Prodnik 2014; Kitchin 2017; Srnicek 2017; Fuchs 2019).

This is to name only some of the most prominent issues that recent research has focused on, with many more aspects of our lives affected on a daily basis (Willson 2016). There seems to be little doubt algorithms now play one of the central roles in almost all spheres of society, from politics and economy to culture and interpersonal relationships, subsequently raising various types of ethical issues (Mittelstadt et al. 2016; Coeckelbergh 2020).

In digital environments algorithms overlap and mutually influence each other, forming what can be considered layered algorithmic systems or ensembles of algorithms (cf. Kitchin 2017, 18–21). In this chapter I will not explain individual algorithms in an abstract manner, but rather focus on the key characteristics and social consequences of such ensembles of algorithms in their current hegemonic social form (for practical reasons I will simply refer to them as algorithms). This will hopefully shed some light on the reasons for their increasing social influence.

All technologies are inevitably embedded in – and influenced by – the social context in which they are developed, so my analysis will consider ensembles of algorithms as part of the competitive and inherently unstable capitalist society (Streeck 2012), or to put it more narrowly, as part of digital capitalism (Fuchs and Mosco 2015; Fuchs 2019). My contribution therefore aims to provide some answers on how algorithms work in digital capitalism, what are the key reasons for this and what is their impact for society at large. Focusing on digital capitalism assumes a theoretical framework of the political economy of communication, which points at the power asymmetries in society in an overarching manner, while taking on board the fact there is nothing 'natural' in these characteristics of algorithms. It also helps to move the analysis beyond abstract notions that have a limited explanatory value in specific historical contexts.

Understanding Ensembles of Algorithms in Capitalism

In contrast to many other topics there is a large degree of overlapping in how authors define algorithms. Bunz (2014, 7), for example, notes that an algorithm is 'a set of rules to be followed by calculations'. This definition does not differ significantly from either Bucher's (2017, 31), in which an algorithm 'is just another term for those carefully planned instructions that follow a sequential order', or Kitchin's (2017, 14), for whom algorithms are 'sets of defined steps structured to process instructions/data to produce an output'. In this sense all computer software and digital technologies are fundamentally composed of algorithms (ibid.). Even though they were put forward by social scientists, such definitions are quite abstract and cannot explain by themselves why the social impact of algorithms has been so significant in recent years, especially since there is no inherent technical necessity for their increased omnipresence.

As already noted, my aim is not to look for universal characteristics of algorithms – even if that were possible or made sense in social sciences – but to understand them as part of the existing historical epoch, where they are bundled together in vast and overlapping digital ensembles, predominantly under the control of powerful capitalist corporations. Not to interpret them as technical or mathematical constructs, but through their social causes, purposes and consequences when implemented and executed (cf. Mittelstadt et al. 2016, 2–3). This choice comes close to popular definitions of algorithms and has obvious downsides. It leaves much room for ambiguity and either risks making the scope of analysis too expansive, or puts too much focus solely on what could be called 'mega-algorithms', while ignoring the more basic ones. It is exactly these algorithms, however, that are most influential and consequential. As such, they must be subject to thorough scrutiny.

Algorithms as Narrow Artificial Intelligence

Before continuing I must note that for the purposes of this chapter I consider algorithms as part of a narrow form of artificial intelligence. They have limited autonomy beyond the tasks which they were made for. While the so-called Artificial General Intelligence has the capacity to behave intelligently in a wide variety of contexts and use knowledge in novel situations, emulating intelligence of human beings, it remains in the realm of speculation (Boden, 2016; Dyer-Witheford et al. 2019, Ch. 1; Mitchell 2019, Ch. 3; Coeckelbergh 2020). What is sometimes called narrow AI, however, is already widely present and exists in our everyday lives. It can be connected to algorithmic processes that normally address narrow tasks, which means that their application cannot be generalised to other domains of functioning. State of the art AI still lacks real understanding and thus flexibility to operate outside the frontiers of their own design (ibid.).

Because algorithms 'don't know what they don't know' human beings have an advantage especially in complex communication, expert thinking, and creative tasks (Diakopoulos 2019, 29–30, 122; cf. Bunz 2014, 17; Mitchell 2019). It is also very challenging for computers to perform non-routine tasks, as human beings have large reservoirs of tacit and contextual knowledge, which they are not even aware of (so-called Polanyi's paradox). The situation is similar with our most basic and unconscious sensorimotor abilities, including walking, manipulating objects or understanding complex language, which may be very simple tasks for human beings but are amongst the biggest challenges for engineers (Moravec's paradox). These issues are currently generating considerable engineering bottlenecks (see Frey 2019, 233–236).

The currently dominant paradigm in AI is machine learning, for example, via artificial neural networks which try to mimic human brains. Instead of being built top-down as a set of logical rules for handling data, machine learning systems use an inductive approach for finding patterns, which are often based on statistical calculations and probability. A statistical pattern-recognition approach presupposes pattern extraction from data, with these systems creating their own models of inference. Developed solutions are therefore based on the data itself and on what these algorithms have previously learned (see Boden 2016; Mitchell 2019; Dyer-Witheford et al. 2019, 8–15; Bridle 2018, Ch. 6).

The fact that machines now continuously learn on data means that actors and institutions, that have access to quantitatively more and/or qualitatively better information, are in an advantageous position. They can improve the quality, effectiveness and capacities of their algorithms. This is an important point I will return to when describing the characteristics of algorithms in digital capitalism. Nonetheless, as a narrow form of AI these systems can currently generalise only on data they were trained for, and therefore merely simulate real intelligence.

Embedding Algorithms in Capitalism

To say that algorithms have to be considered as part of capitalist society may seem fairly inconsequential, as I noted at the start of this chapter. But this is a system with certain tendencies and basic characteristics that influence all phenomena operating within it. Even though these tendencies can be countered or partially neutralised in many ways, most obviously through politically enacted regulation, they are the result of existing and dynamic social structures. They do not pre-determine the outcomes, but they do set the framework and delimit the level of possibilities within that system (cf. Collier 1994). In other words, capitalism has a specific logic in how it operates, and the impact of that logic can be identified and analysed in various phenomena that work within this system.

A concise definition of capitalist society is provided by Streeck (2012), who argues that this 'is a society that has instituted its economy in a capitalist manner, in that it has coupled its material provision to the private accumulation of capital, measured in units of money, through free contractual exchange'. Similar to social scientists in the 19th century, he emphasises that there cannot be any strict empirical separation between society and economy because of their interrelatedness. Furthermore, economic relations are constantly attempting to consume non-economic relations through commodification, since this is a system that needs to expand constantly, paradoxically staying stable only when being in movement (cf. Prodnik 2016). Competitiveness, permanent revolutionising – presupposing continuous change, innovations, instability and uncertainty – and expansion of capital are therefore part and parcel of this system and influence all social relations (Streeck 2012, 5–9).

In a critical and holistic approach of the political economy of communication, it would thus not only be disadvantageous, but quite impossible to completely dissemble algorithms from the wider capitalist context. Major ensembles of algorithms today are developed and owned by some of the biggest corporations in the world (Mosco 2014). Alphabet (Google), Facebook, Microsoft, Apple or Amazon might be seen only as tech companies, but they are expanding into and influencing numerous other branches of the economy and consequently our lives. Many other companies that primarily function as digital platforms, such as Uber or Airbnb, have brought similar economic disruption not only to the most prominent geographic locations, but also to peripheral ones (cf. Srnicek 2017). Even the automotive company Tesla views itself first and foremost as an innovative tech company, conspicuously basing its headquarters in Silicon Valley.

It is not only that algorithms play one of the most important roles in all of the cases mentioned above, they also clearly demonstrate it has become impossible to speak of 'digital-only' projects, that would somehow be separated from the non-digital world. In digital capitalism many formerly clear borders and demarcation lines have converged or completely collapsed as commodification seeps into every part of our lives, social practices and relations (Prodnik 2016).

Even though major digital corporations are in many ways breaking new ground, they are not entirely dissimilar from corporations of the old. They are in perpetual quest of either short-term or long-term profits and new areas where they could expand to, while constantly struggling to innovate and increase their market share. These very basic pursuits largely delimit the manner in which they design algorithms and why they are developed in the first place (cf. Mager 2012; Gillespie 2014, 176–177). Bilić (2018) points out that this is one of the central reasons why algorithms cannot be seen simply as technical artefacts. In the case of Alphabet, for example, algorithms are 'also business strategies for market control and dominance' (ibid. 71). This should be taken aboard before pondering further about the characteristics of algorithms, as it is relevant throughout the chapter.

Characteristics of Algorithms and their Structural Reasons

A study of the literature on algorithms cited in the previous sections makes it possible to define four basic characteristics of algorithms in digital capitalism: (1) opacity and obfuscation, (2) datafication, (3) automation, and (4) instrumental rationalisation. There are both structural reasons for these characteristics as well as wider consequences they could have on social relations and social totality. While these characteristics can be analytically separated, they are thoroughly interconnected in practice and frequently reinforce each other. The key point of emphasis mentioned earlier is that these characteristics should not be seen as universally inherent to algorithms, since they are to a considerable degree a product of the existing social order – digital capitalism. To put it differently, in a different political-economic context, there could be other structural reasons at play, thus leading to changes in these basic characteristics or at least in their prominence.

Opacity and Obfuscation

The first fundamental characteristic of algorithms is opacity and obfuscation, which is mainly an outcome of their secrecy and restrictiveness, but also of technological complexity and multiplicity. In essence, how algorithms actually operate is to a large degree incomprehensible and difficult to understand, often even for experts. While we have basic ideas about the major algorithms, discerning details of how exactly they work, what data they are collecting, how it is used, why certain results finally appear, or who has access to them, is much more difficult or even impossible. Pasquale (2015), for example, notes that algorithms are secretive and restrictive black boxes. This seems like an apt metaphor, since it denotes both a recording device and 'a system whose workings are mysterious; we can observe its inputs and outputs, but we cannot tell how one becomes the other' (ibid. 3). Even though algorithms have wide-ranging consequences for the shape and direction of our societies, this means they are 'opaque and inaccessible to outside critique; and their parameters, intent and assumptions indiscernible' (Willson 2016, 4).

There are three major structural reasons for this characteristic. Firstly, they are privately owned and subject to various types of intellectual property rights (copyright, patents, trademarks, etc.), that generally presume secrecy (ibid.). As emphasised by Pasquale (2015, 61), 'the huge companies resist meaningful disclosure, and hide important decisions behind technology, and boilerplate contracts' (cf. Kitchin 2017, 20). While most companies that own algorithms have obvious commercial reasons to keep them opaque – intellectual work, as part of them, can serve as an important market advantage when competing with other companies (cf. Bilić 2018) – making them completely transparent could also lead to security breaches and attempts of manipulation. An obvious example is the gaming of search engines by rogue websites.

Even if there was full transparency on how algorithms work, most internet users would have serious problems if they tried to meaningfully comprehend them (Obar 2020; Willson 2016, 10). A digital divide can therefore be seen as the second structural reason for opacity, one that can be connected to the lack of expert digital literacy and programming knowledge of lay users. Power asymmetries and social inequalities are leading to exclusion in the digital as well as non-digital spheres as most people have vast difficulties with much more basic online understanding than complexities of algorithmic procedures. A poll conducted by the Pew Research Center (2018), for example, revealed that the majority of Facebook users had almost no knowledge of how their news feeds work. One can therefore only imagine how far from being able to understand the complexities of algorithms most internet users are.

Comprehending how algorithms operate, however, is not difficult only for the average user of the internet but even for experts. Several factors contribute to this, including the fact that they are 'always somewhat uncertain, provisional and messy fragile accomplishments', often worked on by large teams of programmers that constantly change and have a highly specialised division of labour between them, making an overview of the whole programming process difficult (Kitchin 2017, 18, 21; Bridle 2018, 40). In an analysis of financial algorithms, Pasquale (2015, 123; cf. 32), for instance, noticed how sometimes 'black boxes are so effective they even 'fool' their creators'. This is the third structural reason for opacity, which can be closely connected to the fact we are speaking about large ensembles of layered algorithms that are interconnected, mutually influencing each other and constantly expanding, multiplying and changing (cf. Willson 2016). Furthermore, results of sub-symbolic AI systems, for example deep learning neural networks that are increasingly used in machine learning, are very difficult to unpack, because they do not use symbols and a logic that is understandable to human beings (Mitchell 2019).

Datafication

Most algorithms make little sense or cannot even operate without the data which they process. Algorithmic decisions are made on this basis, meaning that the effectiveness of algorithms is 'strongly related to the data sets they compute' (Bunz 2014, 7). This is why, as I noted earlier, data is an increasingly important commodity in digital capitalism.

There are, again, several reasons for this characteristic, the most obvious being that decisions made by algorithms are based on computational calculations that can usually be made only via quantifiable information. This inherent dependency on data has as a consequence a clear tendency towards the datafication of various practices and relations. Or to put it differently, the transformation of social reality and the world into structured data schemes that generally exclude nuance and wider context (Diakopoulos 2019, 117). Datafication should not be seen as something static, but as a continuous process; it is an important characteristic of major algorithms because they require constant flows of data (i.e. Big Data) to perform their key functions – a tendency so prominent because of the increased computing power and the near total ubiquity of digital networks and their tracking capacities (Prodnik 2014).

It could certainly be argued that dependency on data holds true for algorithms as such, but it seems clear they truly gained relevance only with the availability of large troves of information that enable complex inferences, correlations and predictions drawn on a large scale (and beyond the scope and capacities of human beings). This also leads us to the second structural reason for datafication, one that is closely related to the first one: there is a constant need for enhanced capabilities and effective algorithms in a competitive environment, at least if they are to produce improved results and operate better. Frey (2019, 304) notes that 'data can justly be regarded as the new oil'. Even though this illustration is overused and can at best be understood as a somewhat faulty metaphor, it is true that 'as big data gets bigger, algorithms get better' (ibid.). With the development of machine learning, exposing algorithms to more examples leads to improvements in how they perform tasks (Mitchell 2019, Ch. 6).

Datafication has become so pronounced only with the development of digital capitalism, where the constant need for more and more data has become both a self-perpetuating cycle and one of the central factors in the production process. If we borrowed a phrase from the Marxist conceptual apparatus, we could say that the sum total of the forces of production in a specific historical context had to be developed to a certain level to make this a real possibility. Viewing this as a universal characteristic of algorithms would therefore be difficult, since they do not need – as a necessity – vast quantities of data to perform the most basic functions. It is only when they become crucial in the production process that this becomes the case. Institutions and actors employing algorithms typically do so because they want to predict large scale trends, patterns and risks or try to exert control, again pushing towards datafication to come closer to this objective. This is closely related to the properties of digital capitalism and can be seen as the third structural reason for datafication (cf. Mosco 2014; Prodnik 2014).

Automation

Datafication is directly associated with the automation of processes, functions and decision-making. Automation is what makes algorithms so appealing in the first place, but it also 'means that information included in the database must be rendered into data, formalized, so that algorithms can act on it automatically' (Gillespie 2014, 170). Automation and datafication are therefore mutually intertwined. An attempt of automating decisions structurally pushes towards more datafication, with access to (more) data often enabling more intensive and extensive automation.

Automation is a very discernible characteristic that makes algorithms into an interesting option for various actors and institutions. It enables them to 'make high-quality decisions, and to do so very quickly and at scale' (Diakopoulos 2019, 19). This can lead both to a qualitative jump in acceleration of functions or procedures and their considerable scalability. Again, it may seem perfectly reasonable to claim this characteristic is universally inherent to algorithms and has little to do with digital capitalism; however there are three interrelated, but analytically distinguishable structural factors that counter this seemingly commonsensical notion.

First, algorithms and their capacities can bring increased competitive advantages to the companies employing them. Fractions of seconds, incomprehensible to humans, can bring literally millions in financial trading or vast reductions in labour costs (Pasquale 2015, Ch. 4; MacKenzie 2017; Bridle 2018, 106–109).

Second, existing resources can be put to a much better use and can help move decision-making process beyond the limitations that are inherent to human beings. Formerly laborious operations are simplified and made easy, often literally a click away. Today, it seems almost incomprehensible to imagine a manual harvesting of data, the indexing of the internet or non-automated searching, which would be performed solely by human beings and did not happen instantly.

Third, and related to the previous reasons, increased overall efficiency is another enticing prospect for firms when applying algorithms. Attempts of automation have of course been a constituent part of the industrial capitalist society and there is a constant tendency on the part of capital to replace workers with machines and reduce labour costs (Dyer-Witheford et al. 2019, Ch. 1; cf. Marx 1867/1990). Algorithms thus present merely another step in that direction, but quite possibly a qualitatively new one, since human beings increasingly have difficulties competing in cost, efficiency and speed with automated systems, leaving the door open for the automation of entire labour processes.

Instrumental Rationalisation

Development and application of technologies is highly dependent on the wider power relations, values and ideologies in society. While this is no place to go into the theoretical nitty gritty of it, most critical approaches today acknowledge this fact. The political economy of communication, for example, emphasised the historical interrelation between the US military and industry in the development of ICTs, and how these technologies were remodelled to fit capitalist social relations (Prodnik 2014; Dyer-Witheford et al. 2019, 3; Fuchs 2019). Even if we would disregard the long history of ICTs – which, after all, have to be seen as constitutive for the development of AI – development of algorithms is usually just a means to reach a very narrowly defined end. In other words, it is highly rationalised and instrumentalised. As an example, we can take the digital social media that critical authors view first and foremost as attention machines, aimed at catching and producing consumers. But as noted by Vaidhyanathan (2018, 87), how they work goes beyond distraction and exhaustion. It also dehumanises users, since 'it treats us each as means to a sale rather than as ends in ourselves'.

Algorithms cannot be seen merely as technical artefacts, because this would fail to explain their social role and influence – something I underscored earlier in the chapter. As stressed by Bilić (2018, 60), they must be seen as expressions of a specific technological rationality predominant in capitalism. They are embedded within it 'as a mode of production, a specific form of capitalism–algorithmic capitalism' (ibid.). Other kinds of technological rationalisations are always possible, but in capitalism imperatives of this system are predominantly imposed on technologies. Examining how search engines are constructed, Mager (2012) for instance noticed that boundaries emerging from capitalist social relations were woven into the practicalities and the operation of algorithms behind them. This produced specific biases and altered the whole digital ecosystem, producing what she called algorithmic ideology.

The capitalist logic can therefore be seen as the main structural reason for instrumental rationalisation, being one of the fundamental characteristics of algorithms (cf. Fuchs 2019, 59). This describes not only the central reason behind this characteristic, but in many ways also key reasons for opacity, datafication and automation. For Fuchs (2009, 8), instrumental reason is 'oriented on utility, profitableness, and productivity', with its objectives reduced to cost-benefit calculations. At least to a degree this is present in all characteristics delineated above, and all are therefore contributing to the intensification of instrumental rationalisation.

The Algorithmic Logic and its Social Consequences

It is possible to identify a range of conceivable consequences resulting from the four characteristics of algorithms. A schematic overview of structural reasons and their social consequences is provided in Table 12.1. The list of consequences is far from exhaustive and their relation to the characteristics may not be as direct as presented. It should, however, capture at least the essential features of what can be called algorithmic logic in digital capitalism.

What I am describing here are tendencies that are real in the abstract, but can in practice be counteracted in various ways, hence forming potential counter-tendencies that would limit their actual social impact. Social struggles and protests could for instance force governments into political measures that would lead to a shortening of the workday, which in turn could ease the pressure on unemployment; regulation could curb mass surveillance and data harvesting; court decisions could limit the dominant market position of certain corporations and its platforms or put a stop to facial recognition and so on. Various countermeasures are to be expected, but they should not lead us to believe these tendencies were not 'real' or present in the first place (cf. Collier 1994).

Incomprehensibility, Lack of Accountability and Preserving the Status Quo

An important consequence of opacity and obfuscation of algorithms is their incomprehensibility for both lay users and often also for experts. In essence, these are secretive artefacts in more than one meaning of the word, since their complexity is an important and non-intentional contributing factor to

Table 12.1: Algorithmic logic in digital capitalism.

Structural reasons		Basic characteristics	Social consequences	
Intellectual Property Rights		Opacity and obfuscation	Incomprehensibility and secrecy	Reproducing status quo; reinforcing power asymmetries and inequalities
Digital divide (expert illiteracy)			Lack of oversight and control	
Multiplication, layering, constant change			No democratic accountability and legitimacy	
Decisions made via mathematics and rules		Datafication	Intensified quantification and concentrated ownership of data	
Improving capabilities and effectiveness			Mass and ubiquitous surveillance as a norm; privacy breaches	
Predicting trends and exerting control			Constructed and biased processes appearing as objective and neutral	Naturalisation
Increasing competitive advantages		Automation (of processes, functions and decisions)		
Increased efficiency of labour, processes and decisions			Further push in social acceleration	
Better use of existing resources, moving beyond limitations of human beings			Changes in the (re)production of space	
			Wide-ranging effects on employment and labour relations	
Profit seeking; competitiveness; capitalist colonisation of technologies	↓ Opacity	Instrumental rationalisation	Social atomization; commodification; control/domination; reification; alienation	
	↓ Datafication			
	↓ Automation			

their secrecy (Coeckelbergh 2020, Ch. 8). It is often the case that we do not understand how algorithms function and interrelate, what exactly their operation encompasses, what impact they have on our lives and under what conditions this happens. This is why algorithms can lead to results and consequences that might not be intended in the first place and sometimes cannot even be adequately explained.

There have been numerous cases of encoded biases in algorithms such as racist profiling or sexism (Bridle 2018, 142), which were a consequence of comparable biases historically existing in society. The poet Joy Buolamwini, for example, criticized them in a project *AI, Ain't I A Woman* (www.notflawless.ai), which focused on grave failures of facial recognition when it came to black women. A myriad of such incidents demonstrates both that algorithms are far from neutral artefacts, a point I return to later, but also that even their designers in many cases have difficulties understanding why certain results materialised in the first place. In one of the more famous instances, Grindr was linked as a related application to an app which was aimed at finding sex offenders, revolting the LGBT community. What is telling is that this and many other similar examples usually surprised designers of algorithms themselves. Increasingly sophisticated, extensive and complex algorithmic processes mean that 'unintended and unanticipated consequences are an obvious, and will be an increasingly common, outcome' (Willson 2016, 8).

According to Pasquale (2015, 14) strategies of secrecy and obfuscation in algorithms are aimed at the consolidation of power and wealth. This cannot be seen as surprising, since applying intellectual property rights can bring the owners competitive advantages. Many authors have advocated for more transparency as a solution to the problem of algorithms being black boxed, which is a worthy cause. But making them transparent does not in itself bring any meaningful understanding of how they function (Willson 2016; Coeckelbergh 2020, Ch. 8; Obar 2020). Since they are layered and complex systems, these properties represent difficulties even for experts, not to mention activist groups or regulators that would have the capacity to curtail them. Neither does the transparency of algorithms touch on an even graver problem – the commodification and privatisation of data.

Social scientists have started warning about the dangers of algorithmic procedures for democracy, especially when it comes to the influence of the biggest digital social networking sites (Moore 2018; Vaidhyanathan 2018). This happened because nobody beyond their owners has a real oversight over how these algorithms are used, even though they have vast influence over the political process. This lack of accountability can be seen as a fundamental problem, because legitimation is at the core of all publicly relevant decisions in democratic societies (cf. Coeckelbergh 2020, Ch. 10). Pasquale (2015, 16) goes even as far as to claim that 'transactions that are too complex to explain to outsiders may well be too complex to be allowed to exist'. In his opinion the information imbalances have gone too far, particularly since corporations that own algorithms have become the new sense-makers of our world. The Big Data they collect brings big dangers, with even the smallest of oversights potentially creating life-changing reclassifications in algorithmic decision-making processes (for examples see Eubanks 2017; Coeckelbergh 2020).

What seems apparent, therefore, is that datafication in many ways helps to reproduce or even reinforce the status quo, and with it the existing power asymmetries and social inequalities.

Mass Ubiquitous Surveillance in a World of Privatised Data

It goes almost without saying that a logical consequence of the ever-present datafication is mass and ubiquitous surveillance, with severe breaches of privacy as the final outcome. In the last two decades digital surveillance via various ICTs has practically become a norm, which led to a formation of a whole new research subfield with Surveillance studies. In 2013 this became an even more vigorously debated topic after the Snowden revelations. There is no need to repeat the main arguments of these debates, beyond the fact that digital surveillance opens the door for new ways of sorting, classifying, profiling, segregating and thus also discriminating people, which again reinforces existing inequalities and brings about new social disadvantages (see Prodnik 2014; Mosco 2014; Fuchs 2019).

It is essential to underscore that data is not simply one of the resources in what Srnicek (2017) calls platform capitalism or what Fuchs (2019) defines as Big Data capitalism. It has become *the* resource for major companies, especially in the case of machine learning (Coeckelbergh 2020). This is why datafication – and correspondingly Big Data and mass surveillance – is not simply an optional thing. If you block surveillance the effectiveness of algorithms plummets and many of the existing business models start to collapse. Surveillance and privacy breaches are therefore a necessary part of the algorithmic logic in digital capitalism. They are not a bug but a constituent feature that powers its development.

A continuous push for datafication also brings about a highly unequal concentration of the ownership of the data, which is syphoned off using digital surveillance (cf. Mosco 2014). These information inequalities are even more intensive than in the past, when Perelman (2002, 5) pointed out that 'intellectual property rights have contributed to one of the most massive redistributions of wealth that has ever occurred'. He based this assessment on the fact they were owned almost exclusively by the rich and the powerful. Processes occurring with algorithmic datafication, however, are accentuating and intensifying this problem even further.

Neutrality of Algorithms and their Naturalisation

Various studies have attested to the fact that algorithms are far from neutral technical artefacts (Willson 2016, 9–10). This is both because human biases are present in their development and because they are created with certain purposes in mind, for example 'to create value and capital; to nudge behaviour and structure preferences in a certain way' (Kitchin 2017, 18). Who creates algorithms and with what underlying aims is far from irrelevant. Facebook's algorithms, for instance, highly value content that arouses strong emotional reactions (Vaidhyanathan 2018), which was not a neutral engineering decision of its creators. While this may make Facebook into a powerful tool for motivation – but especially for grabbing users' attention – it also means it 'is a useless tool for deliberation' (ibid. 132, 144). It mainly sparks shallow declarations and potentially destabilises democratic procedures.

As noted by Diakopoulos (2019, 18) 'the judgments that algorithms make are often baked in via explicit rules, definitions, or procedures that designers and coders articulate when creating the algorithms'. They are of course neither neutral nor objective, but what is true is that 'they will apply whatever value-laden rules they encode consistently' (ibid.). This contributes to the illusion of their neutrality, even though it merely moves discrimination, prejudices, stigmatization and disadvantages upstream (Pasquale 2015, 35).

How Google sorts its search results or how Facebook organises its news feed may seem self-evident and almost natural for their users, a normal order of how things stand, even though it was based on very real human decisions of how these platforms present and sort content. Many of our activities and practices of course become naturalised when they become part of our everyday routines and we accept them without necessarily questioning the power relations constitutive for them (Willson 2016, 2). It would indeed be impossible to live our lives if we always scrutinised every step we took, even the most mundane ones. However, this is not the only reason for naturalisation of algorithms; both datafication and automation are contributing to the fact that algorithmic decisions appear neutral. They are based on objective calculative procedures, which indeed have no intrinsic biases in themselves. This 'mathematical, computational and rational design', which is necessary for algorithms and is acquired through datafication, creates 'an aura of universality of reason, an aura of calculable, efficient and truthful solutions to given problems' (Bilić 2018, 59). Since these decisions are simultaneously also automated, they obtain what could be called epistemic purity, and with it a halo of authority (Diakopoulos 2019, 118). This can be related to a phenomenon called automation bias, in which automated procedures are perceived as more trustworthy than nonautomated ones or even our own experiences (Bridle 2018, 40). This is particularly true in case of ambiguous situations, since 'automated information is clear and direct, and confounds the grey areas that muddle cognition' (ibid.).

Temporal and Spatial Changes

Automation will also produce noticeable changes in temporal compression and the way space is (re)produced. When processes, decisions and functions increasingly become automated, they also get accelerated. Especially in the case of intangibles, the level of acceleration facilitated by algorithms cannot be measured only quantitatively. The change is primarily qualitative in nature, because it leads beyond limitations inherent to humans. The most obvious example is High-Frequency Algorithmic Trading in the financial markets, which is highly unstable and has been largely automated, with human traders becoming more or less obsolete. Decisions are now made in microseconds, leading to 'one of the most dramatic increases in speed in recent times', going 'beyond those perceptible by human beings' (MacKenzie 2017, 55; cf. Pasquale 2015, 128–132; Wajcman 2015, 17–21).

Nevertheless, acceleration in trading cannot be explained solely with technological advances in algorithms. It was a result of carefully planned decisions at the time these algorithms were designed, with speed purposively at the core of how they function (see MacKenzie 2017). It would therefore be both theoretically and empirically wrong to make a direct causal connection between acceleration and changes in technologies, as if the latter were constructed in a social vacuum. As emphasised by Wajcman (2015, 3), 'temporal demands […] are built into our devices by all-too-human schemes and desires'.

In Rosa's (2013) general theory of modernity, social acceleration is a constitutive and unavoidable part of modern societies, but technological acceleration is only one of the three dimensions in what he calls the acceleration-cycle. The other two are acceleration of social change and acceleration of the pace of life. Technological acceleration is indeed based on technological innovations like algorithms, with competition providing incentives for their development and adoption (what Rosa calls the external economic motor). However, in isolation, technological acceleration could not by itself lead to social acceleration. In most cases new technologies enable us to save time and should therefore – if anything – contribute to a general deceleration. It is only in relation to the other two dimensions and the fact we live in a competitive (capitalist) society that technological breakthroughs in fact lead to social acceleration (ibid.).

In a similar manner, algorithms may actually slow down the way certain sectors function. MacKenzie (2017, 57–58), for instance, discovered that work in the trading sector has slowed down considerably. It became much less hectic, but this was down to the fact that the work itself changed completely. It was not performed by human traders anymore, but by programmers that developed algorithms. Even with such contradictory examples, the general effect of the adoption of algorithms will almost surely be further social acceleration, in line with other similar technological advances.

Algorithms are also changing public and private spaces, and how we perceive and interact with them (Mittelstadt et al. 2016, 1). Algorithms are at the core of smart cities, they are creating new knowledge about space, they are (re)directing traffic, procuring navigation and rewriting how we understand certain geographical locations (Fisher 2020). Alexa's algorithms are, for example, reshaping how we live in our private homes, while Airbnb is fundamentally transforming how people see their dwellings, simultaneously changing city geographies (Munn 2018). In essence, algorithms are already remodelling time and space configurations.

(Un)employment and Automation

Several studies are warning that the current pace of automation could have a serious impact on future unemployment and global labour markets. It is expected that a combination of algorithms, robotics and computers will increasingly make human labour redundant, even without development of Artificial General Intelligence (Coeckelbergh 2020, 136–144). There are many technical problems connected to automation, but they are slowly being overcome with machine learning and by making simple tasks even simpler. This solution was already used in factory automation during the industrial revolution, when previously unstructured tasks were subdivided and simplified. Whereas there is certainly a lot of unwarranted hype connected to algorithms and AI, a long history of technological innovations, identified already by Marx (1867/1990, 562–563), attests to capital's constant tendency to make labour superfluous through automation. As noted by Dyer-Witheford et al. (2019, 4) the 'dismissal of automation as a "charade" is deeply ahistorical'. In the past, 'capital has made people and indeed entire populations disposable'.

A research paper by Frey and Osborne, published in 2013, for example, tried to estimate the probability of computerisation for 702 detailed occupations in which 97 per cent of the American workforce was employed at the time (Frey 2019, 319). They estimated that nearly half of all employments were at risk, with low-income jobs that required lower education to perform hit the hardest (ibid. 319–321). Frey (ibid. 322) analysed other studies and they concurred it was especially unskilled jobs that were most exposed to the risk of automation. A policy brief by OECD (2018) forecasted less drastic impact of automation, with 14 per cent of the jobs in OECD countries highly automatable and 32 per cent facing substantial change in how they are done. But their analysis also warns that the tasks AI cannot do are rapidly shrinking, with some jobs becoming entirely redundant (ibid.).

It is unlikely all occupational areas will go through such a radical transformation in the mid-term as jobs in financial trading (MacKenzie 2017), but it seems that only a few will remain unaffected (Frey 2019, Pt. 5). While estimates regarding the proportion of occupations under direct threat remain speculative and vary because of differences in methodologies, it is highly doubtful they will all be offset by completely new occupations. Collins (2013) is amongst the authors that are convinced capitalist societies are facing the end of the middle-class work as we knew it because of technological displacement. He predicts even starker inequalities. Considering how deeply unequal societies today are, and how uneven ownership of the algorithmic means of production is, we have every reason to be sceptical that the benefits of these processes will be evenly shared by the majority of the population.

Conclusion: Algorithmic Necessity?

Once it is formed, a system takes on a life of its own.

– Haruki Murakami (1Q84)

In a growing number of social domains decisions are influenced or directly made by algorithms. It remains to be seen how far reaching their influence will be in the long-run, but it seems increasingly likely that different corporate actors and state institutions will either adopt algorithms or use them even more widely than they currently do. This tendency can be called *algorithmic necessity*, indicating that it is increasingly inevitable that different institutions will employ algorithms. Their adoption can have significant advantages on the market or can help to 'rationalise' administrative functions, which is always portrayed as a worthy cause in the neoliberal state. Non-adoption can similarly bring disadvantages, as companies that are incapable of innovation fall behind their competitors or simply fail to meet their quarterly goals. When one company uses large quantities of personal data to improve their algorithms in an attempt to gain a competitive edge, others are likely to follow, which forms an almost self-propelling cycle.

What Marx (1867/1990, 433) called 'the coercive laws of competition', this iron cage of capitalist society, will therefore have direct influence on the general expansion of algorithms and how they are developed. Competition between different capitals that are structurally forced to constantly increase their accumulation, for example, pushes them into technological innovation (cf. Streeck 2012, 5). With algorithms, this can lead to increases in productivity (preferably through automation), improvements in efficiency, or speeding up of the circulation of capital. As noted by Wajcman (2015, 17), 'the faster that money can be turned into the production of goods and services, the greater the power of capital to expand or valorize itself. With capitalism, time is literally money, and "when time is money, then faster means better" and speed becomes an unquestioned and unquestionable good'.

The mythological aspects of implementing technological innovations should not be overlooked either, even in the case when they might not be economically rational at all. It is easy to simply dismiss the hype surrounding technological breakthroughs, but in Mosco's (2014, 5) view, such appraisals are mistaken: 'The marketing hype supports myths that are taken seriously as storylines of our time. If successful, they become common sense, the bedrock of seemingly unchallengeable beliefs'. Socially dominant myths acquire their own power and tend to become self-fulfilling prophecies.

In digital capitalism the implementation of algorithms follows the logic of instrumental rationalisation that produces 'irrational results' and 'impoverishes human experience' (Bilić 2018, 59–60). Authors of the Frankfurt School closely related instrumentalisation to the development of capitalism and the predominance of economic rationality in this system. They warned that intensification of these processes will lead to further social atomization, reification, domination and alienation. These are some of the most fundamental consequences of algorithms as artefacts of digital capitalism.

These critical observations should not be taken as some Luddite rejection of technological progress, where the only path is either acceptance of algorithms or their complete rejection. Instead, there is no doubt that algorithms of a different sort can serve democratic means, reduce human toil, reduce inequalities and help to bring about overall improvements in the quality of our lives. But this presupposes their fundamental reimagining in how they are made and for what purposes, together with political struggles that take into account the fact they can – and should – be changed if this is to happen. And this cannot be done without a change in who has control and ownership over these systems. In other words, this presupposes social relations that go beyond those imposed by digital capitalism.

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