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Societal Algorithmification and its Computational Measurement

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Abstract
The digitalization and algorithmification of individual behavior and social conduct have become the dominant socio-technological paradigm of our times. Its all-pervasive applicability modernizes all facets of human life. Computational social science methods have shown to be useful in studying the resulting dynamics by making effective use of the very same computational technologies that constitute the digital paradigm. The proposal of this line of research is to go one step further and not only take advantage of the tools, but also of the theoretical framework of the digital age. Information theory and theoretical computer science gave rise to the digital paradigm and, at the same time, turn out to be useful in its conceptualization and quantification. Variables like 'information', 'predictability', and 'knowledge' become measurable constructs in their own right. This Chapter reviews the underlying theoretical justifications and presents an overview of empirical applications, which include studies of recommender systems, collective dynamics on Wikipedia and the stock market, and the evolution of economic growth.

Keywords: information theory, algorithms, complexity, digitalization, artificial intelligence, complexity.

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Contents

Introduction

Digital technology has infused almost all aspects of our individual and social life. The advancement of our understanding of the digital paradigm has become urgent, as any technological revolution comes with unavoidable side effects, and the collateral damage of digital technology is already widely felt. It includes harm to mental health from social media (Allcott et al., 2020; Eyal, 2014), harm to democratic opinion formation through misinformation (Epstein & Robertson, 2015; Lazer et al., 2018), and commercial exploitation through tailor-made manipulation (Hannak et al., 2014; Nahai, 2013). The discussion about adequate policy responses has just begun and still lacks sufficient research support to be conclusive (Coravos et al., 2019; Hilbert, 2020b; Tutt, 2016).

This Chapter approaches the resulting challenges by proposing that the same conceptualization that created the digital age can also help make sense of it. The methodological tools from computational social science, combined with the theoretical concepts from information theory and theoretical computer science, allow researchers to make a science of the building blocks of the digital age. Concepts like 'data', 'information', 'communication', 'complexity', and 'knowledge' are clearly defined concepts in the theoretical literature that conceptualizes the machines that give rise to the digital age. They can also be used to conceptualize 'social computations' and 'human communication', especially as they merge with digital machines. The "social power of algorithms" (Beer, 2017) leads to many new research questions (Wagner et al., 2021), many of which relate to the particularities of "machine behavior" of artificially intelligent technology (Rahwan et al., 2019) and the emergent "social algorithm, which examines the interplay of social and computational code" (Lazer, 2015, p. 1091).

In the first part of the Chapter, we review a way of theorizing the digital age in terms of traditional innovation theory. In the second part, we review how concepts from information theory and theoretical computer science can be used to measure and quantify the digital age. In both parts, we discuss the logic of the chosen approach, define the dominating terminology, and review what we have learned so far in terms of stylized facts and existing studies.

Theorizing Digitalization and Algorithmification

The current paradigm of societal algorithmification can be framed within the traditional framework of innovation theory, which holds that socio-technological progress is characterized by cumulative creative destruction (Schumpeter, 1939; Freeman, 1990). The current focus on algorithms and knowledge can be seen as the subsequent stage of societal evolution, building on digital information and communication, much like steam-powered industrialization built on water-powered industrialization two centuries earlier (Hilbert, 2020a). Algorithmification does to knowledge processes what digitalization does to information and communication. Just like computation is a process of information and communication (which is illustrated in the traditional setup of a Turing machine (Turing, 1936)),[1] algorithmification builds on the innovations introduced by the digitalization of information and communication, which is a necessary but not sufficient condition. Similar to how 'digitalization' introduces far-reaching changes to fundamental concepts of social reality, including reconfigurations of notions of space and time (Cairncross, 1997), the importance of network structures (Castells, 1999), scale economics (Shapiro & Varian, 1998), and changes in individual and collective identity (Turkle, 1984, 1995), algorithmification leads to fundamental changes in the modus operandi of processes (Hilbert, 2015). It leads to a reorganization of individual and societal dynamics, resulting in the emergence of a jointly biological and computerized social order (Gillings et al., 2016). We now review an innovation theoretic approach to algorithmification and then discuss the newly introduced terminology in more detail.

Approach: innovation theory

On the highest level of aggregation, innovation theory describes social evolution in terms of so-called Schumpeterian long-waves of socio-technological change (Freeman & Louçã, 2002; Kondratieff, 1935; Perez, 2004; Schumpeter, 1939). The different period are historically named after the dominating technological paradigm. The first sequence of innovations focused on transforming material, and included the stone-, bronze-, and iron-ages. The second sequence of long-waves focused on the transformation of energy, and included the water-, steam-, and electricity paradigms of societal modernization. The current sequence focuses on the transformation of information (Hilbert, 2020a), which can also be subdivided into sequential sub-paradigms. During the first decades of the digital paradigm (the 1980s – 2010s), the focus was set on the digitalization of data and communication, which was driven by telecommunication, databases, and digital networks. The current longwave shifts the focus from information to knowledge and algorithms, which focuses on processes (Hilbert, 2020a). It is driven by artificial intelligence, and the internet of smart things, 3D representations, and blockchain technology.

In order to classify as a "long-wave / great surge" of human development (Perez, 2015), algorithmification needs to fulfill characteristic criteria of what economists call a "general-purpose technology" (Helpman, 1998). It needs to exhibit descending costs, extensive supply, boost productivity, and have "all-pervasiveness" (Perez, 1983, p. 361). Algorithms easily clear the bar of the first three criteria, as exemplified by the proliferation of machine learning in the economy (Brynjolfsson & McAfee, 2014; Agrawal et al., 2018).
It is instructive to emphasize how all-pervasive algorithms and the potential areas of applications of algorithmification are. All behavior of living beings lends itself to algorithmic infusion. This is because life tends to follow repetitive routines that often result in stable collective structures. Any repetitive structure unfolding in time is a potential application for algorithmification. "An algorithm is an ordered set of unambiguous, executable steps that define a terminating process" (Brookshear, 2009, p. 205). It is not necessary to understand what an algorithm does in order to have one. Many modern machine learning algorithms are notorious black boxes (Pasquale, 2015). Many social processes are little understood as

[1] A Turing machine is the prototypical abstract model of computation. It consists of a finite-state machine ('the algorithm') that is associated with a storage tape ('information/data') and a 'head' that can read from and write to ('communicate with') the tape following the instructions from the provided algorithm.

well, but they still compute. Algorithmification focuses on systematic approaches to find, expand, fine-tune, and experiment with processes that unfold in time. In this sense, we can essentially think of an algorithm as a structure in time. The focus on building structures in time is the essence of algorithmification. Let us review some of the ongoing efforts in the field of business routines, social habits, cultural conduct, and laws, which are all potential candidates for algorithmification.

Industrial automation promotes the algorithmification of behavioral processes head-on, which often goes under catchphrases like smart industry or industry 4.0 (Hermann et al., 2016). An organization can be conceptualized as an information-processing entity (Galbraith, 1974) made of individual and collective routines (Nelson & Winter, 1985). Organizational routines are "a pattern of behavior that is followed repeatedly, but is subject to change if conditions change" (Winter, 1964, p. 264). As such, organizational routines lend themselves to an algorithmic [if-then] logic. Algorithmification is a potent tool to optimize the end goal of organizational routines, customs, and rules, which have emerged to reduce uncertainty, both in terms of the cognitive load of an organization (fewer surprises), and to coordinate a common understanding that augments collective control (Becker, 2004). The substitution of uncertainty with predictability is one of the main goals of algorithmification (Agrawal et al., 2018). The goal of the seamless integration of enterprise software like ERP (enterprise resource planning) (Jacobs & Weston, 2007), SCM (supply chain management) (Mentzer et al., 2001), and CRM (customer relationship management) (Dyché et al., 2002), with control systems on the machine level (ANSI/ISA-95, 1995), consists in algorithmifying management and production processes throughout the company (Plattform Industrie 4.0, 2018). All of these information systems aim at substituting remaining degrees of uncertainty with predictable information that allows company assets to intelligently coordinate and negotiate needs based on their algorithms guided by business KPI (key-performance-indicators), aka the 'industrial internet of things' (Boyes et al., 2018; Sisinni et al., 2018).

Not only the economy, also society as a whole is made of repetitive processes that lend themselves to algorithmification. Sociological concepts like Bourdieu's 'habitus' (Bourdieu, 1990), Gidden's 'structuration' (Giddens, 1986), Habermas' transition from 'lifeworld' to 'system' (Habermas, 1995), and the social construction of 'habitualization' and institutionalization' by Berger and Luckmann (1967) provide the basis for a deep and wide theoretical literature on the social emergence between individual behavior and social structure that unfolds in time. This literature holds that the reduction of uncertainty is the main driver for the repetitive behavior of individuals and emergent social patterns. Repetition reduces uncertainty about the way of doing things individually and collectively and, therefore, reduces cognitive loads. "The most important gain is that each [member of society] will be able to predict the other's actions. Concomitantly, the interaction of both becomes predictable" (Berger & Luckmann, 1967, p. 57). Predictability is the domain of algorithms. Today's "prediction machines" created the most valued companies in history by predicting the habitus of social media users better than they could predict their own behavior (Frias-Martinez & Virseda, 2013; Hilbert, Barnett, et al., 2019; Wang & Kosinski, 2018; Wu et al., 2015). Persuasive technology created entire industries that add tangible aspects of modern structuration and institutionalization by creating new psychological and social habits (Eyal, 2014; Nahai, 2013). Social media algorithms bind people an average of three hours a day, executing predictably repetitive procedures (GlobalWebIndex, 2020), mainly following the incentive mechanism of algorithmically induced behavior in the form of views and clicks, shares and posts, etc. (Lanier, 2018).

Scholars have also long emphasized the role of culture as an evolving system of rules and habits (Boyd & Richerson, 1985; Richerson & Boyd, 2004). Cultural systems are often modeled with the help of the algorithmic rules of game theory (McElreath & Boyd, 2007), which provide a straightforward recipe for anyone aiming at algorithmifying them (Epstein, 2006). The algorithmification of such cultural norms and conduct leads to the concept of "algorithmic culture" (Dourish, 2016; Hallinan & Striphas, 2016; Striphas, 2015). If societal norms reach an even more mandatory status, they become encoded in law. In the digital age, "code is law" (Lessig, 2000). Similar to laws and regulations in societies running on analog mode, algorithmic code has started to regulate social conduct, often even deciding between the seen and unseen, the possible and impossible, right and wrong, and good and bad (Lessig, 2006). The algorithmification of both cultural norms and official laws can be seen in the example of a self-driving car. The car itself algorithmifies the rules and particular regulations of the processes involved in driving a car: driving on the left or right side, giving priority to the right or first arrival at intersections, etc. It also needs to encode cultural norms such as the socially acceptable distance to other cars (which would be much larger in the U.S. than in many Asian or Latin American countries, for example). Going even further, moral dilemmas like the trolley problem (sacrificing one person to save a larger number, etc.) reveal deeply rooted cultural differences in crucial driving decisions (Awad et al., 2018), which is something that will also need to be algorithmified in self-driving cars.

Last but not least, the "all-pervasiveness" of the potential applicability of algorithmification goes beyond the human realm. Behavioral patterns born from the social emergence of collective multi-agent systems are not unique to humans: flying birds fall in line forming V-shapes; fireflies limit flash in synchrony; ants will predictably converge on the shortest path, etc. (Mitchell, 2011). Complex systems science has modeled these and other collective processes quite successfully as natural algorithms (Chazelle, 2015), because that is what they are, essentially. Going one step further, even the abstraction of all kinds of dynamics in the form of scientific laws can be seen as algorithms. Both algorithms and scientific laws share the ambition to act as "a prescription uniquely determining the course of certain constructive processes" (Markov & Nagorny, 1988, p. 102). Both scientific laws and algorithms can also be used proactively, in an engineering sense, to create and execute processes. "After any step, if we don't have the answer yet, the instructions together with the existing situation will tell us what to do next" (Kleene, 1967, p. 223). This quote talks about mathematical logic in scientific laws, but it is also the definition of an algorithm.

Terminology: digitalization and algorithmification

The suffix '–fication' comes from the Latin facere 'to make, do'. It is used here to emphasize a semantic difference between 'algorithmization' and algorithmification'. The difference is similar to 'digitization' and 'digitalization' (Gartner Glossary, 2022a, 2022b). As shown in Table 1, 'digitization' refers to the process of converting information from analog to digital format, such as scanning a book, transferring a song from vinyl to CD, replacing a paper airline ticket with a pdf, etc.. The essence of the item stays the same. In the same sense, 'algorithmization' refers to a translation from an analog process to digital format without any different-in-kind changes to the process itself, such as paying a bill, transferring established tax filing procedures into a tax software, encoding Newton's 17th century root-finding algorithm into a calculator, etc. Digitization refers to information and communication, and algorithmization to temporal processes. Both consist of a digital replication of what can, in essence, exist in analog form as well.

In contrast, digitalization and algorithmification go beyond mere replication and imply a digital transformation, indicating a qualitative change in form. For example, while the Library of Congress has focused on the 'digitization' of books and the 'algorithmization' of how they can be lent (a digital replication of the existing analogous modus operandi), Jeff Bezos digitalized the business models around books with Amazon.com, which was initially an online marketplace for books. The digital transformation introduced in the book market was as striking that Time Magazine named Bezos the "Person of the year" in 1999, only five years after he founded the company in 1994. Among others, the qualitative changes introduced by the early digitalization of Amazon's book marketplace included mass customization of product portfolios (Da Silveira et al., 2001), the reconfigurations of space and time constraints (Cairncross, 1997) through network structures (Castells, 1999), the exploitations of network effects and scale effects (Shapiro & Varian, 1998), and the creation of a digital identity related to reading habits (Turkle, 1984, 1995).

Table 1: Digitalization and Algorithmification matrix

	Information & Communication	Knowledge & other Algorithms
Replication	digitization	algorithmization
Transformation	digitalization	algorithmification

While the scanning of books is a typical example of 'digitization', a typical example of 'algorithmization' is a tax software. The 'code of law' (in this case the tax law) has existed for centuries, and tax software replicates it in digital format. There is no (and there should not be any) qualitative change, much like there should not be any qualitative change in a scanned book. While the book represents a 'structure in space' (on paper or in silicon), a tax law represents a 'structure in time' (a recipe), which is essentially an algorithm, "an ordered set of unambiguous, executable steps that defines a terminating process" (Brookshear, 2009, p. 205). When the algorithm halts, the tax declaration has been computed. The algorithmification of the process of paying taxes would imply a qualitative change in the system. In this case, this must include changing the law that defines the process of paying taxes. While this has not (yet) happened, blockchain technology is one possible candidate to introduce qualitative changes to the way tax systems work, including transformation resulting from transparency, efficiency, data integrity, and security (Collosa, 2022).

Areas of application where the algorithmification of processes has already led to noticeable transformations include early adopters of artificial intelligence (i.e. machine learning), computer simulations (i.e. digital twins), and decentralization (i.e. sharing economy models or decentralized blockchain applications). The very goal of machine learning is to search for the optimal algorithm based on the provided data and goal (Domingos, 2015). The systematic use of bots on Wikipedia is an example the algorithmification of encyclopedia editing with the help of machine learning trained natural language algorithms (Geiger, 2011; Tsvetkova, et al. 2017). The use of machine learning and simulations for stock trading exemplified the digital transformation of processes on the stock market (Chaboud et al., 2014; Hendershott & Moulton, 2011). 3D simulations and digital twins are the frontrunner application of the metaverse (Ball, 2022) and provide a myriad of virtual flexibility to explore new ways to go about things. The sharing economy, as exemplified by the victory marches of Uber in the transportation industry and Airbnb in the hospitality industry, is another example of algorithmification (Cheng, 2016). The sharing economy satisfies an existing demand in a new way with the help of digital processes. Another leading example of algorithmification are applications that involve so-called 'big data', such as in retail application based on the tailor-made matching between the supply and demand of individuals based on an automated analysis of digital trace data in real-time (Mayer-Schönberger & Cukier, 2013; McAfee & Brynjolfsson, 2012). As social media has become the leading news source for people (Gottfried & Shearer, 2016), its persuasive algorithms (Fogg, 2002) have algorithmified how people get to know and consume news.

Of course, there are no clear criteria to determine when the essence of a process stays the same (replication) or if significant innovation occurs (transformation). It is a question of degree and emphasis. We might as well argue that the matching between supply and demand on the stock market or by retailers has already been done before the reign of algorithms, executed in the minds and hearts of salespeople. The suffix '–fication' emphasizes the qualitative changes produced by algorithms, much in line with Schumpeter's (1939) classical "creative destruction" of innovation. Such paradigm-changing transformations also lead to the characteristic side-effects of technological revolutions (Perez, 1983, 2004), which simple conversions would unlikely produce. In our example of social media algorithms, these reach from mental health challenges (Nodder, 2013; Orlowski, 2020) to the challenge of filter bubbles and misinformation (Lazer et al., 2018; Pariser, 2011).

What we have so far: stylized theoretical facts

While the applicability of algorithmification is far-reaching, it also counts on some common characteristics that allow for the formulation of stylized facts (propositions) and even some tentative predictions (corollaries). First and foremost comes the recognition that '*individual behavior and social processes are inherently algorithmic*' (proposition 1). These might be probabilistic algorithms, but, nevertheless, reliable patterns emerge on the individual and collective levels. The effect of algorithmification is that '*algorithmification creates predictable structure in time*', which reduces temporal uncertainty when going from the past into the future (proposition 2). This is useful, as it is in line with life's tendency to increase evolutionary fitness through the reduction of uncertainty because '*uncertainty and predictable structure can be substituted against each other*' (proposition 3), as defined by information theory (Chaitin, 1966; Kolmogorov, 1968; Shannon, 1948) (more on this in the next section). Based on these three propositions, we can conclude that there are incentives that '*implicit social procedures will increasingly become explicit algorithmic code*' (corollary A).

Based on the powerful theorems and tools derived over the past decades from information theory, we can also make some rather surprising predictions about the nature of this transformation. One refers to the different effects of algorithmification on uncertainty in society. While proposition 2 holds that '*algorithmification creates predictable structure in time*', at the same time, '*algorithmification increases uncertainty at any given moment*' (proposition 4), as it fine-grains available options, offering many more choices than before. Combining propositions 2 and 4 leads to the prediction that '*algorithmification simultaneously increases predictability and uncertainty*' (corollary B). We have more choices at any given point in time, but our dynamic behavior is more prescribed, even if in a probabilistic stochastic fashion. As we will discuss below, the reason is that algorithmification increases what statistical mechanics calls 'statistical complexity', which leads us to the question of how to measure the different aspects of algorithmification.

Measuring Digitalization and Algorithmification

The core argument of this second part of this Chapter is that the theoretical conceptualizations underlying digitalization and algorithmification (information theory and theoretical computer science) not only enabled the engineering of the digital age but also afforded us the analytical methods and theoretical frameworks to analyze and study it. The same theoretical frameworks that allowed engineers to create the digital age turn out to be also helpful for social scientists to make sense of it.

Approach: from technological theory to social theory

The ideas and theoretical concepts underlying the technological and engineering aspects of digitalization and algorithmification had been worked out decades before they reshaped society. One of the leading figures in laying the theoretical groundwork was Claude Shannon (1916-2001), the so-called "father of the information age" (Roberts, 2016). Among other contributions, he single-handedly conceptualized the fundamental unit of the digital age: the bit. The proposed limits of Shannon's (1948) ground-breaking source coding theorem were not achieved until the discovery of turbo-codes in the mid-1990s (Berrou et al., 1993), almost half a century later, which then enabled 3G/4G mobile communications in the early 2000s. Similarly, his proposal to apply Boolean algebra to logic gates (Shannon, 1938) came to fruition only decades later with the design of digital circuits in microprocessors in the 1970s. His proposal to "make more use of brutal calculation than humans" in "programming a computer for playing chess" (Shannon, 1950, pp. 273–274), was finally demonstrated by the dominance of chess machines in the late 1990s (Newborn, 2012) (for more of Shannon's illustrious life and achievements, see (Gleick, 2011; Levinson et al., 2020)).

In the decades after the engineering "puzzle-solving" had concluded (Kuhn, 1962, p. 35), the resultant digital networks created an unprecedented informational flood sloshing back and forth between humans (Hilbert, 2011, 2018b). This communication flood filled databases with inconceivable amounts of digital trace data about society (Hilbert, 2017b), which companies and governments have started to exploit (Mayer-Schönberger & Cukier, 2013; McAfee & Brynjolfsson, 2012; Zuboff, 2019). Extraordinary computational power became available to help human brains make sense of this overload of empirical evidence (Anderson, 2008; Halevy et al., 2009). The resulting research opportunities for a better understanding of the involved dynamics are exploited by so-called computational social science (Cioffi-Revilla, 2014; Conte et al., 2012; Contractor, 2018; Hilbert et al., 2019; Lazer et al., 2009; Pentland et al., 2005; Watts, 2007). This places us currently in a situation where we are already surrounded by the machines we created, but still lack a thorough understanding of them and the social emergence provoked by their application, but we use them and their output to advance our understanding. In other words, we are studying technology with the help of the same technology to understand the socio-technological paradigm they created.

While this might sound peculiar, it is rather the norm than the exception in light of the usual process of scientific discovery (Kuhn, 1962). "Many of the most general and powerful discoveries of science have arisen, not through the study of phenomena as they occur in nature, but rather, through the study of phenomena of man-made devices, in products of technology, if you will. This is because the phenomena in man's machines are simplified and ordered in comparison with those occurring naturally, and it is these simplified phenomena that man understand most easily" (Pierce, 1980, p. 19). Our understanding of hydrodynamics does not come from studying fish, but from building ships; our understanding of thermodynamics does not stem from studying fire, but because Carnot wondered why gun barrels turned hot when moving a cannonball through them. Steam locomotives were up and running two decades before Carnot published his thermodynamic 'Reflections' (Carnot, 1824). Likewise, the details of aerodynamics were not derived from studying birds, but from constructing airplanes. Our understanding of electromagnetism does not originate from the study of lightning, but from electrical engineering. Michael Faraday built his first electric motor ten years before writing down his first equation, and Maxwell's more general equations of electromagnetism clarified things only 40 years later.

Likewise, algorithmification holds the potential to understand the age-old tendency of individual and collective pattern formation and execution. By studying human conduct and social dynamics as they occur in "man-made devices, in products of technology", we can reveal hidden patterns that were previously tacit "as they occur in nature" (Pierce, 1980, p. 19).

The proposal of this line of research consists of carrying out the conclusion all the way. Just like it is helpful to use computational methods to understand computational systems, the invitation is also to make use of computational theory to make sense of it. Without an adequate theoretical framework, it is unlikely that we identify adequate measures and indicators to quantify what is happening since measurements inevitably depend on the underlying theory (Greenwald, 2012). The stuff of our algorithmically infused age is made off are components like 'data', 'information', 'communication', and 'knowledge'. Information theory and theoretical computer science provide mathematically clearly defined conceptualizations of these and related notions (Hilbert, 2016).

In short, we went from the theoretical deductions in the 1940s-70s that led to the creation of the technology to their social applications during the 1980s-2010s, and now face the challenge of understanding the resulting socio-technological paradigm. This line of research proposes to take advantage of the same theoretical concepts that created the paradigm in the first place, bringing the interplay between science and engineering full circle.

Terminology: information, communication, knowledge

Before reviewing some of the applied measures of digitalization and algorithmification, we quickly review some of the basic theoretical notions behind formal definitions of 'data', 'information', 'communication', and 'knowledge', as defined in information theory and theoretical computer science (Cover & Thomas, 2006; Kolmogorov, 1968; Li & Vitanyi, 1997; MacKay, 2003; Pierce, 1980).

In information theory, **data** is usually defined as symbols without any meaning or value. It refers to any registered distinction of an identified set. This perceivable difference can be visual, auditory, tactile, olfactory, gustatory, imagery, or dynamic in time, etc. The binary digit is the most fundamental differentiation between signals and refers to the existence [1] or non-existence [0] of some signal (typical hardware implementations include electrical current in a microchip, a beam of light in a fiber optic cable, or a wave in a radio-frequency band). Data refers to differentiable symbols.

Information is defined as a "difference which makes a difference" (Bateson, 1972, p. 272). The difference it makes is that it reduces uncertainty. If some kind of symbol shows a difference (for example, either 1 or 0), but there is absolutely no surprise or uncertainty in it, it does not reduce uncertainty and therefore is no information. The ingenuity of Shannon's definition of information as the opposite of uncertainty is ingenious and subjective, as it depends on the uncertainty of the decoder. In an information-theoretic sense, there might not be any information when it would be communicated to you that 'all good things will come to an end' (you likely already knew that: so much is certain), but there would be information in communicating when that occurs. Communicating this proverbial adage still contains data (almost three dozen characters of data), and there might be some uncertainty reduction in when and by whom it is communicated to whom, etc.

Since uncertainty can be quantified with the mathematical tools of probability theory, its opposite, information, can also readily be quantified with the same framework, making information theory a branch of probability theory (or, as some scholars convincingly argue, it provides the base for probabilities to emerge (Caves, 1990; Rissanen, 2010)). Shannon defined one bit of information as 'that which reduces uncertainty by half'. Shannon's informational bits can be extracted from data's binary digits by 'compression'. Compressing data into information takes out all redundant data and leaves only those differences that effectively reduce uncertainty. During the period of digitalization between 1980 and the early 2000s, the compression from redundant data into compressed information was the main driver for the global growth of the world's information and communication capacity (Hilbert, 2014). The remaining quantity after optimal compression is called the "entropy of an information source" (Shannon, 1948), where entropy is a measure of the uncertainty of the source. This is enshrined in Shannon's famous "source coding theorem" (Cover & Thomas, 2006).

Communication is defined by Shannon's "noisy channel coding theorem" (Cover & Thomas, 2006), which is "one of the most remarkable pieces of mathematics of the last century" (MacKay, 2012, sec. 2). The theorem derives a measure known as 'mutual information', and quantifies what information the sender and receiver have in common. Communication is the shared information between sender and receiver. In that sense, it quantifies the result of error-free communication. Communication aims at creating a common understanding, which requires the same interpretation of the communicated content. Anything else would be noise and miscommunication.

Summing up, Shannon's (1948) framework (which is surprisingly readable for its profoundness) proposes to quantify information as the opposite of uncertainty and communication as reduced uncertainty between subjects (variables). This makes intuitive sense: if you have uncertainty, you do not have information, while the communication of information from one to the other is the process of uncertainty reduction between them and the increase in a common understanding.

Digitalization of societal processes is based on the concepts of information and communication. It involves internet connections, mobile phones, social networking sites, e-commerce platforms, and large databases. Algorithmification goes one step further and shifts the focus from information to **knowledge**. In the related theoretical literature, it is defined as a procedural kind of information. Much in line with the definition of an algorithm, knowledge implies a step-by-step recipe for doing something. It is a program. Similar to probabilistic information, if there is knowledge, there is no doubt, there is a process or procedure that defines how things go from one to the next. Knowledge describes something (deterministic), while information reveals it (probabilistic). Theoretically, the right measure to quantify the amount of knowledge contained in a deterministically unfolding process has been established by Kolmogorov (1941, 1968) and independently developed by Solomonoff (1964) and Chaitin (1966). It is known as "Kolmogorov complexity" (Li & Vitanyi, 1997), or any combination of the names of the three aforementioned luminaries (Crutchfield, 2012). In line with the later developed 'minimum description length principle' (Grunwald, 2007; Rissanen, 1978), it defines the amount of 'knowledge' in an algorithm to be equal to the minimum number of symbols needed to efficiently describe an object or process to a specific level of detail.

Interestingly, an "amazing" (Cover & Thomas, 2006, p. 463) and "beautiful" (Li & Vitanyi, 1997, p. 187) fact leads to a theorem that equates both Shannon's information and Kolmogorov's knowledge (Caves, 1990; Grunwald & Vitanyi, 2004; Hilbert, 2016; Leung-Yan-Cheong & Cover, 1978; Zurek, 1989). More precisely, their quantities approach each other, asymptotically, but despite its intricate mathematics, this result also makes intuitive sense: if I communicate x bits of information to you, the revealed surprise reduces your uncertainty by x bits. Alternatively, I could give you an optimized algorithm to run a program that leads you to the same result: you then reduce the uncertainty not through communication, but through computation (Hilbert, 2016). While the second alternative might require additional energy to run the algorithm (and the discovery of the algorithm to begin with), the plain amount of information, in terms of the number of bits involved, should be the same in both cases. Bits measure how much uncertainty is reduced, and it should not matter if this is achieved by revelation (the selection of one message among many possible messages) or by computation (the construction of a message in contrast to all other possible messages). An optimized algorithm should reduce the same amount of uncertainty (have the same number of bits) as is measured by Shannon's source entropy. Otherwise, the theory would not be consistent (or at least one side of the equation would not be optimized or asymptotic).

What we have so far: stylized empirical facts

The application of these concepts to study our socio-technological systems comes with several benefits (Hilbert, Liu, et al., 2019): it provides a series of fundamentally derived measures that stood the test of time; it naturally captures nonlinearities in the arising patterns; it allows to continue the longstanding social science practice to calculate statistical significance and effect size separately; and, maybe most important, it provides for the possibility to deduce additional conclusions that piggyback on hundreds of theorems, lemmas, corollaries, and proofs. This turns out to be useful in conceptualizing and measuring digitalization and algorithmification.

A straightforward application is to use Shannon's entropic definition of information to measure how much information there is in the world and to contrast that with the amount of mere data stored or communicated. The number of symbols stored and communicated can be estimated by simply multiplying the number of devices (infatructure) with their performance (hardware). Content compression then converts binary digits into uncertainty reducing bits (Hilbert & López, 2011; Hilbert 2017b, 2018b). This is a contribution of software. For the period of 1986-2007, which hallmarks the period of digitization and digitalization, it turns out that software compression was the main driver of the global information explosion (Hilbert, 2014). It contributed more than the increasing number of devices or the better hardware performance to the world's technological capacity to store and to telecommunicate information. This was achieved by compressing data to its entropic rate and to only communicate 'that which reduces uncertainty' (at the entropy rate of the source, as defined by Shannon's source coding theorem).

Going one step further, we can use Shannon's (1948) notion of a noisy communication channel to model an algorithm as an input-output system. In both cases, information goes in, and information comes out. Shannon's engineering goal was to create noiseless input-output telecommunication channels with as little distortion as possible (Pierce, 1980).
On the contrary, today's algorithmic channels are often highly proactive and shape the conversion according to commerce or national security interests. The goal is different, but the same theoretical framework and its fundamental measures can be applied to quantify throughput and the degree of transformation (Hilbert, Liu, et al., 2019). In the case of a recommender algorithm, entropies can be used to measure the distortion between ingoing personal trace data and the outgoing content recommendations. In the case of a natural language processing neural net, mutual information can be used to quantify the relation

between ingoing words and outgoing numbers. Furthermore, drawing on a fundamental information-theoretic theorem known as the data-processing inequality (Cover & Thomas, 2006, p. 36), it can be deduced that no manipulation of information (whatsoever clever) can increase the amount of information that is being processed in this transformation. This can be used to infer even unobserved quantities in the input-output transformation of algorithms, such as YouTube and Twitter's recommender engines and IBM Watson's natural language processing suite (Hilbert, Liu, et al., 2019).

More sophisticated measures can quantify directed information flow. If entropy is akin to a variance in more traditional linear statistics (both measuring the uniformity/skewness of a distribution), and mutual information to a covariance or correlation (both measuring the dependence of two variables), so-called transfer entropy (Schreiber, 2000) is akin to Granger causality (Amblard & Michel, 2011). Transfer entropy has been used to measure directed information flows in social media (Baek et al., 2005; Borge-Holthoefer et al., 2016; Ver Steeg & Galstyan, 2012) and also, in a concatenated form, to quantify how much information flows from humans to algorithms and then back to influence the human (Hilbert, Ahmed, et al., 2018). Effortlessly capturing all involved nonlinearities in the communication between humans and recommender algorithms, we showed, for example, that joy in videos promoted by YouTube's recommendations is prevalent in emotional polarization, while sadness and fear play significant roles in emotional convergence (Hilbert, Ahmed, et al., 2018). As such, information theoretic measures can also be used to guide societal design aspects of social algorithms (they are already used to design engineering aspects of them, as evidenced by the fact that information theory is the only mathematical prerequisite for the leading textbook on "Deep Learning" besides linear algebra (Goodfellow et al., 2016)).

While the previous three examples focused on rather static setups, one of the hallmarks of the application of information theory in recent decades has been its applications to dynamical systems theory and complex adaptive systems (Bialek et al., 2001; Crutchfield, 1994; Crutchfield & Feldman, 2003; James et al., 2011; Kolmogorov, 1959; Sinai, 1959). Digital footprints, left behind by every digital step people take, allow us to observe and analyze large-scale social dynamics to a degree not possible before. Information theory can quantify aspects of emergent structures. For example, focusing on the algorithmification of computer-supported collaborations on crowdsourcing platforms, we examined how much of the social emergence of turn-taking between contributors on Wikipedia, GitHub, and OpenStreetMap stems from participation frequency statistics and how much from temporal sequence dynamics (Hilbert, James, et al., 2018). Some contributors are more active than others (static frequency counts), which creates a predictable structure, while the contribution of others is triggered by temporal events, which also adds to overall predictability through patterns in time. We found trade-offs in the importance of static and dynamic contributions to predictable structures and calculated that about three-fourths of the total predictability of turn-taking stemmed from participation frequencies, while one-fourth originated from temporal dynamics. The longstanding information theoretic theorem known as Fano's inequality (Fano, 1961) was essential to derive these results, as was the availability of 'big data', since information-theoretic measures converge rather slowly (we used over 1.5 million contributions from over 200 thousand contributors in 38 projects).

Information theory's application to dynamical systems also led to a series of interesting reformulations of the fundamental equations of evolutionary population dynamics (Frank, 2009, 2012; Kelly, 1956; Rivoire, 2015), especially for bet-hedging dynamics of populations in varying environments (Donaldson-Matasci et al., 2010; Hilbert, 2017a; Rivoire & Leibler, 2011) and portfolio theory (Barron & Cover, 1988; Haccou & Iwasa, 1995). With the help of these reformulations, it can be shown that information (in bits) is a quantifiable ingredient of evolutionary growth: "the more you know, the more you can grow" (Hilbert, 2017c). In biological evolution, population growth during risk-spreading is exactly equal to the reduction in uncertainty about the environment (Donaldson-Matasci et al., 2010). The more information the evolving population has about its uncertain environment, the more it can adjust to it and increase evolutionary fitness. Mutual information emerges as the natural measure to assess this communication channel between evolving populations and the environment. The application of this framework to the digital paradigm provides a mathematical model that exemplifies (and quantifies) how data-based predictions about an uncertain environment (such as done by e-commerce platforms or social media sites) can be turned into economic growth (Hilbert, 2017c). It provides a formal model for the information-based business model behind the commercial use of data-driven "prediction machines" (Agrawal et al., 2018). Thanks to information theory, information derived from predictions becomes a measurable ingredient for economic growth. For example, we quantified how much chocolate and diet products vendors could increase sales by predicting informational patterns in demand for these complementary products throughout the year (think about the winter holidays and new year's resolutions) (Hilbert, 2017c). This provides a theoretical framework, hands-on measures, and a formal mathematical model for the promise and practice of this aspect of the digital paradigm.

Going beyond digitalization toward algorithmification, it becomes useful to follow the extensions of information theory into theoretical computer science. This has mainly been established by Kolmogorov's seminal work (Kolmogorov, 1941, 1963, 1968). The further development of Kolmogorov's theoretical conceptualizations (Li & Vitanyi, 1997) has become a cornerstone of modern statistics and data science, especially in the form of the minimum description length principle (Grunwald, 2007; Rissanen, 1978), which holds that shorter descriptions are more likely to be true descriptions of the observed phenomena. One practical application is the white-box machine learning approach known as "computational mechanics" (Crutchfield, 2012, 2017; Shalizi & Crutchfield, 2001). It provides several ways to derive the unique, minimally complex and maximally predictive model of a temporal sequence. The derived measure is a sufficient statistic and is known as statistical complexity, and the actual model an ε-machine ("epsilon-machine") (Crutchfield & Young, 1989). Its mathematical solidity arises from "three optimality theorems that say it captures all of the process's properties: prediction: a process's ε-machine is its optimal predictor; minimality: compared with all other optimal predictors, a process's ε-machine is its minimal representation; uniqueness: any minimal optimal predictor is equivalent to the ε-machine." (Crutchfield, 2012, p. 20). In short, predictive state machines are special because they are optimally predictive, minimally complex, and unique in both previous traits (a sufficient statistic). As such, predictive state machines "capture the essential computational aspects of the data stream by virtue of the following instantiation of Occam's razor" (Crutchfield & Young, 1989, p. 106).

We applied these theoretical constructs to quantify the effects of algorithmification on Wikipedia and the stock market. Both are quite advanced in the algorithmification of their processes. For the stock market, algorithmic trading executes between 50% and 90% of the trades. For Wikipedia, it was estimated that editing bots make between 3% and 16% of the edits. We studied them by analyzing one billion trades of eight foreign exchange currency pairs (2007–2017) (Hilbert & Darmon, 2020b) and over 4.5 million edits from over 500 Wikipedia articles (Hilbert & Darmon, 2020a). 'Big data' is important to calculate these slowly converging measures. As predicted by the theory of algorithmification (see section, "What we have so far: stylized theoretical facts"), on the one hand, the automated behavior of algorithms makes dynamics more predictable. Traders and editors employ algorithms to reduce the local uncertainty of their work with the help of algorithmic pattern creation (e.g. the automated sale of a currency at a certain price pattern, or the automated reversion of vandalism on Wikipedia). On the other hand, however, we find that the overall process becomes less predictable. We show that algorithmification is the main explanatory variable that leads to the simultaneous increase of both predictability and uncertainty. In short, users introduce algorithms to make dynamics more simple and predictable but end up with large-scale dynamics that are more complex and uncertain.

This might sound counterintuitive, but can be explained by the complementarity between entropy and statistical complexity (Hilbert & Darmon, 2020b, p. 20). The main source of confusion for our intuition is the fact that we instinctively assume that there is a finite amount of uncertainty, and that we will eventually saturate it all with our predictive power. The currently dominating machine learning paradigm feeds on aspects of the correct insight that uncertainty can be replaced by predictable structures. However, at the same time, we the digital paradigm usually fine-grains reality, which increases uncertainty. This is not a mathematical necessity, but often seem to occur in practice. The existence of more intricate structural patterns often leads to more possible states and transitions between these states. Figuratively speaking, instead of saturating some kind of metaphorical finite space of uncertainty with predictable structure, algorithmic complexity seems to grow in a space of uncertainty. Reality is not a finite space to be saturated with knowledge, but an expanding space, in which we ever advance to new levels. The new structure digs deeper into a more fine-grained level of reality, where more uncertainty emerges. There are plenty of new patterns to be explored in the milliseconds of trading fractions of a penny, and in the various ways of automating editing dynamics. One might imagine an increasing surface that gets in touch with ever more possibilities, as the complexity of the dynamic grows. The more complex structure we build into socio-economic dynamics, the more options open up for uncertainty (based on the newly built structure). While we resolve previous levels of uncertainty (nobdy can make money on betting on the dollar in the stock market), we open up new levels of more fine-grained uncertainty (many possibilities and uncertainties open up when doing high-frequency trading on the micro-dollar level). Similar to editing dynamics. While the previous uncertainty related to vandalism of Wikipedia articles has been eliminated by policing bots, bots also added an array of new patterns to editing dynamics of Wikipedia. In short, algorithmification creates more complexity, which leads to predictable patterns and more uncertain options among them.

Conclusion

This Chapter argued that the theoretical concepts and measures that laid the foundation of the digital age, can also help us in making sense of it. Concepts like information, predictability, and complexity have formal definitions in the literature of information theory and theoretical computer science, and they can help us make sense of the ongoing transformations of digitalization and algorithmification.

The theorems, corollaries, lemmas, and proofs of information theory and its elaborations have not only created the digital age, but can also inform social science reasoning about our current societal dynamics. At the same time, human societies are not machines, and therefore, there is still more work to be done, also on the theoretical front. For example, multivariate information theory will require much more elaboration to be better applicable to the social sciences (Hilbert, 2021). Social systems are inherently interconnected systems consisting of many interrelated parts. Empirical methods in the social sciences often work with dozens of variables, including multiple regression, ANCOVAs and MANCOVAs, and structural equation models. In information theory, the main workhorse is still Shannon's bivariate setup of the sender and receiver, while a third variable continues to create confusion among scholars (James et al., 2019; Lizier et al., 2018; Williams & Beer, 2010). No widely accepted consensus has yet been established on how best to deal with information decompositions and with multivariate information theory measures.

Given the tight relationship between theory and methods (Greenwald, 2012), and the more flexible way of approaching both due to computational social science (Hilbert, 2018a), it is important to note that "theories may also benefit from integrating data and measurements into the theory construction process" (Wagner et al., 2021, p. 202). Much work still remains to be done in the measurement and theorizing of societal algorithmification. The methods from computational social science, and the theoretical constructs of information theory and computer science can provide some of the basic building blocks to continue to dig deeper.

Further readings

We refer the reader to Cover & Thomas (2006) as the leading textbook on information theory. For a pop-science recount of the history and influence of Claude Shannon’s information theory, please see the book by Gleick (2011), or the documentary film by Levinson et al. (2020). Crutchfield developed the measure of statistical complexity, and provides an overview article in Crutchfield (2012). Finally, for a less formal overview of information theoretic definitions and bet-hedging applications, see Hilbert (2016), and for a social science application of statistical complexity, see Hilbert & Darmon (2020).

References

Agrawal, A., Gans, J., & Goldfarb, A. (2018). *Prediction Machines: The Simple Economics of Artificial Intelligence*. Harvard Business Press.

Allcott, H., Braghieri, L., Eichmeyer, S., & Gentzkow, M. (2020). The Welfare Effects of Social Media. *American Economic Review*, *110*(3), 629–676. https://doi.org/10.1257/aer.20190658

Amblard, P.-O., & Michel, O. J. J. (2011). Relating Granger causality to directed information theory for networks of stochastic processes. *ArXiv:0911.2873*. http://arxiv.org/pdf/0911.2873.pdf

Anderson, C. (2008, June 23). The End of Theory: The Data Deluge Makes the Scientific Method Obsolete. *Wired Magazine*, *Science: Discoveries*. http://www.wired.com/science/discoveries/magazine/16-07/pb_theory

ANSI/ISA-95. (1995). *ANSI/ISA-95* (Enterprise-Control System Integration). International Society of Automation (ISA). https://en.wikipedia.org/w/index.php?title=ANSI/ISA-95&oldid=1033371154

Awad, E., Dsouza, S., Kim, R., Schulz, J., Henrich, J., Shariff, A., Bonnefon, J.-F., & Rahwan, I. (2018). The Moral Machine experiment. *Nature*, *563*(7729), 59–64. https://doi.org/10.1038/s41586-018-0637-6

Baek, S. K., Jung, W.-S., Kwon, O., & Moon, H.-T. (2005). Transfer Entropy Analysis of the Stock Market. *ArXiv:Physics/0509014*. http://arxiv.org/abs/physics/0509014

Barron, A. R., & Cover, T. M. (1988). A bound on the financial value of information. *IEEE Transactions on Information Theory*, *34*(5), 1097–1100. https://doi.org/10.1109/18.21241

Bateson, G. (1972). *Steps to an Ecology of Mind*. Random House, New York.

Becker, M. C. (2004). Organizational routines: A review of the literature. *Industrial and Corporate Change*, *13*(4), 643–678. https://doi.org/10.1093/icc/dth026

Beer, D. (2017). The social power of algorithms. *Information, Communication & Society*, *20*(1), 1–13. https://doi.org/10.1080/1369118X.2016.1216147

Berger, P. L., & Luckmann, T. (1967). *The Social Construction of Reality: A Treatise in the Sociology of Knowledge* (First Thus). Anchor.

Berrou, C., Glavieux, A., & Thitimajshima, P. (1993). Near Shannon limit error-correcting coding and decoding: Turbo-codes. 1. *Technical Program, Conference Record, IEEE International Conference on Communications, 1993. ICC '93 Geneva*, *2*, 1064–1070 vol.2. https://doi.org/10.1109/ICC.1993.397441

Bialek, W., Nemenman, I., & Tishby, N. (2001). Predictability, Complexity and Learning. *Neural Computation*, *13*, 2001.

Borge-Holthoefer, J., Perra, N., Gonçalves, B., González-Bailón, S., Arenas, A., Moreno, Y., & Vespignani, A. (2016). The dynamics of information-driven coordination phenomena: A transfer entropy analysis. *Science Advances*, *2*(4), e1501158. https://doi.org/10.1126/sciadv.1501158

Bourdieu, P. (1990). *The Logic of Practice*. Stanford University Press.

Boyd, R., & Richerson, P. J. (1985). *Culture and the Evolutionary Process*. University Of Chicago Press.

Boyes, H., Hallaq, B., Cunningham, J., & Watson, T. (2018). The industrial internet of things (IIoT): An analysis framework. *Computers in Industry*, *101*, 1–12. https://doi.org/10.1016/j.compind.2018.04.015

Brynjolfsson, E., & McAfee, A. (2014). *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*. (MP3 Una edition). Brilliance Audio.

Cairncross, F. (1997). *The Death of Distance: How the Communications Revolution Will Change Our Lives* (Other Printing Edition). Harvard Business Press.

Carnot, S. (1824). *Réflexions sur la puissance motrice du feu et sur les machines propres à développer atte puissance*. Bachelier Libraire.

Castells, M. (1999). *The Information Age, Volumes 1-3: Economy, Society and Culture*. Wiley-Blackwell.

Caves, C. (1990). Entropy and Information: How much information is needed to assign a probability? In W. H. Zurek (Ed.), *Complexity, Entropy and the Physics of Information* (pp. 91–115). Westview Press.

Chaboud, A. P., Chiquoine, B., Hjalmarsson, E., & Vega, C. (2014). *Rise of the Machines: Algorithmic Trading in the Foreign Exchange Market*. The Journal of Finance, 69(5), 2045–2084. https://doi.org/10.1111/jofi.12186

Chaitin, G. J. (1966). On the Length of Programs for Computing Finite Binary Sequences. *Journal of the ACM (JACM)*, *13*, 547–569. http://doi.acm.org.libproxy.usc.edu/10.1145/321356.321363

Chazelle, B. (2015). An Algorithmic Approach to Collective Behavior. *Journal of Statistical Physics*, *158*(3), 514–548. https://doi.org/10.1007/s10955-014-1140-6

Cioffi-Revilla, C. (2014). *Introduction to Computational Social Science*. Springer. http://www.springer.com/de/book/9781447156604

Conte, R., Gilbert, N., Bonelli, G., Cioffi-Revilla, C., Deffuant, G., Kertesz, J., Loreto, V., Moat, S., Nadal, J. P., Sanchez, A., Nowak, A., Flache, A., San Miguel, M., & Helbing, D. (2012). Manifesto of computational social science. *European Physical Journal - Special Topics*, *214*, 325–346. https://doi.org/10.1140/epjst/e2012-01697-8

Contractor, N. (2018). How Can Computational Social Science Motivate the Development of Theories, Data, and Methods to Advance Our Understanding of Communication and Organizational Dynamics? *The Oxford Handbook of Networked Communication*. https://doi.org/10.1093/oxfordhb/9780190460518.013.7

Coravos, A., Chen, I., Gordhandas, A., & Dora Stern, A. (2019). We should treat algorithms like prescription drugs. *Quartz*, *Ideas*. https://qz.com/1540594/treating-algorithms-like-prescription-drugs-could-reduce-ai-bias/

Cover, T. M., & Thomas, J. A. (2006). *Elements of Information Theory* (2nd Edition). Wiley-Interscience.

Crutchfield, J. P. (1994). The calculi of emergence: Computation, dynamics and induction. *Physica D: Nonlinear Phenomena*, *75*(1–3), 11–54. https://doi.org/10.1016/0167-2789(94)90273-9

Crutchfield, J. P. (2012). Between order and chaos. *Nature Physics*, *8*(1), 17–24. https://doi.org/10.1038/nphys2190

Crutchfield, J. P. (2017). The Origins of Computational Mechanics: A Brief Intellectual History and Several Clarifications. *ArXiv:1710.06832 [Cond-Mat, Physics:Nlin]*. http://arxiv.org/abs/1710.06832

Crutchfield, J. P., & Feldman, D. (2003). Regularities unseen, randomness observed: Levels of entropy convergence. *Chaos: An Interdisciplinary Journal of Nonlinear Science*, *13*(1), 25–54.

Crutchfield, J. P., & Young, K. (1989). Inferring statistical complexity. *Physical Review Letters*, *63*(2), 105–108. https://doi.org/10.1103/PhysRevLett.63.105

Da Silveira, G., Borenstein, D., & Fogliatto, F. S. (2001). Mass customization: Literature review and research directions. *International Journal of Production Economics*, *72*(1), 1–13. https://doi.org/10.1016/S0925-5273(00)00079-7

Donaldson-Matasci, M. C., Bergstrom, C. T., & Lachmann, M. (2010). The fitness value of information. *Oikos*, *119*(2), 219–230. https://doi.org/10.1111/j.1600-0706.2009.17781.x

Dourish, P. (2016). Algorithms and their others: Algorithmic culture in context. *Big Data & Society*, *3*(2), 2053951716665128. https://doi.org/10.1177/2053951716665128

Dyché, J., O'Brien, M. M., & Dych,ˇ Jill. (2002). *The CRM Handbook: A Business Guide to Customer Relationship Management*. Addison-Wesley Professional.

Epstein, J. M. (2006). Remarks on the Foundations of Agent-Based Generative Social Science. In L. Tesfatsion & K. L. Judd (Eds.), *Handbook of Computational Economics* (Vol. 2, pp. 1585–1604). Elsevier. https://doi.org/10.1016/S1574-0021(05)02034-4

Epstein, R., & Robertson, R. E. (2015). The search engine manipulation effect (SEME) and its possible impact on the outcomes of elections. *Proceedings of the National Academy of Sciences*, *112*(33), E4512–E4521. https://doi.org/10.1073/pnas.1419828112

Eyal, N. (2014). *Hooked: How to Build Habit-Forming Products*. Penguin.

Fano, R. M. (1961). *Transmission of Information: A Statistical Theory of Communications*. M.I.T. Press.

Fogg, B. J. (2002). Persuasive technology: Using computers to change what we think and do. *Ubiquity*, *2002*(December), 5:2. https://doi.org/10.1145/764008.763957

Frank, S. A. (2009). Natural selection maximizes Fisher information. *Journal of Evolutionary Biology*, *22*(2), 231–244. https://doi.org/10.1111/j.1420-9101.2008.01647.x

Frank, S. A. (2012). Natural selection. V. How to read the fundamental equations of evolutionary change in terms of information theory. *Journal of Evolutionary Biology*, *25*(12), 2377–2396. https://doi.org/10.1111/jeb.12010

Freeman, C. (1990). *The Economics of Innovation*. Edward Elgar Publishing. https://econpapers.repec.org/bookchap/elgeebook/550.htm

Freeman, C., & Louçã, F. (2002). *As Time Goes By: From the Industrial Revolutions to the Information Revolution*. Oxford University Press, USA.

Frias-Martinez, V., & Virseda, J. (2013). Cell Phone Analytics: Scaling Human Behavior Studies into the Millions. *Information Technologies & International Development*, *9*(2), 35–50.

Galbraith, J. R. (1974). Organization Design: An Information Processing View. *Interfaces*, *4*(3), 28–36. https://doi.org/10.1287/inte.4.3.28

Gartner Glossary. (2022a). *Definition of Digitalization—Gartner Information Technology Glossary*. Gartner. https://www.gartner.com/en/information-technology/glossary/digitalization

Gartner Glossary. (2022b). *Definition of Digitization—Gartner Information Technology Glossary*. Gartner. https://www.gartner.com/en/information-technology/glossary/digitization

Geiger, R. S. (2011). The Lives of Bots (SSRN Scholarly Paper ID 2698837). *Social Science Research Network*. https://papers.ssrn.com/abstract=2698837

Giddens, A. (1986). *The Constitution of Society: Outline of the Theory of Structuration* (Reprint). Univ of California Pr.

Gillings, M. R., Hilbert, M., & Kemp, D. J. (2016). Information in the Biosphere: Biological and Digital Worlds. *Trends in Ecology & Evolution*, *31*(3), 180–189. https://doi.org/10.1016/j.tree.2015.12.013

Gleick, J. (2011). *The Information: A History, a Theory, a Flood*. Pantheon.

GlobalWebIndex. (2020). *GlobalWebIndex—Audience Insight Tools, Digital Analytics & Consumer Trends* (Social Media). GlobalWebIndex. https://www.globalwebindex.com

Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep Learning*. MIT Press.

Gottfried, J., & Shearer, E. (2016, May 26). *News Use Across Social Media Platforms 2016*. Pew Research Center's Journalism Project. http://www.journalism.org/2016/05/26/news-use-across-social-media-platforms-2016/

Greenwald, A. G. (2012). There Is Nothing So Theoretical as a Good Method. *Perspectives on Psychological Science*, *7*(2), 99–108. https://doi.org/10.1177/1745691611434210

Grunwald, P. D. (2007). *The Minimum Description Length Principle*. The MIT Press.

Grunwald, P. D., & Vitanyi, P. (2004). *Shannon Information and Kolmogorov Complexity*. https://arxiv.org/abs/cs/0410002#

Habermas, J. (1995). *Theorie des kommunikativen Handelns* (7th ed.). Suhrkamp Verlag.

Haccou, P., & Iwasa, Y. (1995). Optimal Mixed Strategies in Stochastic Environments. *Theoretical Population Biology*, *47*(2), 212–243. https://doi.org/10.1006/tpbi.1995.1009

Halevy, A., Norvig, P., & Pereira, F. (2009). The Unreasonable Effectiveness of Data. *IEEE Intelligent Systems*, *24*(2), 8–12.

Hallinan, B., & Striphas, T. (2016). Recommended for you: The Netflix Prize and the production of algorithmic culture. *New Media & Society*, *18*(1), 117–137. https://doi.org/10.1177/1461444814538646

Hannak, A., Soeller, G., Lazer, D., Mislove, A., & Wilson, C. (2014). Measuring Price Discrimination and Steering on E-commerce Web Sites. *Proceedings of the 14th ACM/USENIX Internet Measurement Conference (IMC'14)*. http://personalization.ccs.neu.edu/PriceDiscrimination/Research/

Helpman, E. (1998). *General Purpose Technologies and Economic Growth*. MIT Press.

Hendershott, T., & Moulton, P. C. (2011). Automation, speed, and stock market quality: The NYSE's Hybrid. *Journal of Financial Markets*, 14(4), 568–604. https://doi.org/10.1016/j.finmar.2011.02.003

Hermann, M., Pentek, T., & Otto, B. (2016). Design Principles for Industrie 4.0 Scenarios. *2016 49th Hawaii International Conference on System Sciences (HICSS)*, 3928–3937. https://doi.org/10.1109/HICSS.2016.488

Hilbert. (2018a, July 12). *UCCSS (University of California Computational Social Science): Intro1 Background: Vol. min 41:27-min 82:37*. https://www.youtube.com/watch?v=GXono1qamgc

Hilbert, M. (2011, December 7). Mapping the dimensions and characteristics of the world's technological communication capacity during the period of digitization. *Working Paper*. 9th World Telecommunication/ICT Indicators Meeting, Mauritius. http://www.itu.int/ITU-D/ict/wtim11/documents/inf/015INF-E.pdf

Hilbert, M. (2014). How much of the global information and communication explosion is driven by more, and how much by better technology? *Journal of the Association for Information Science and Technology*, *65*(4), 856–861. https://doi.org/10.1002/asi.23031

Hilbert, M. (2015). *DT&SC 5/6-11: Algorithmification: Vol. UC-wide online course*. University of California. https://www.youtube.com/watch?v=XpaQOLuWv7k

Hilbert, M. (2016). Formal definitions of information and knowledge and their role in growth through structural change. *Structural Change and Economic Dynamics*, *38*, 69–82. https://doi.org/10.1016/j.strueco.2016.03.004

Hilbert, M. (2017a). Complementary Variety: When Can Cooperation in Uncertain Environments Outperform Competitive Selection? *Complexity*. https://doi.org/10.1155/2017/5052071

Hilbert, M. (2017b). Information Quantity. In *Encyclopedia of Big Data* (pp. 1–4). Springer, Cham. https://doi.org/10.1007/978-3-319-32001-4_511-1

Hilbert, M. (2017c). The More You Know, the More You Can Grow: An Information Theoretic Approach to Growth in the Information Age. *Entropy*, *19*(2), 82. https://doi.org/10.3390/e19020082

Hilbert, M. (2018b). Communication Quantity. In *Encyclopedia of Big Data* (pp. 1–6). Springer, Cham. https://doi.org/10.1007/978-3-319-32001-4_512-1

Hilbert, M. (2020a). Digital technology and social change: The digital transformation of society from a historical perspective. *Dialogues in Clinical Neuroscience*, *22*(2), 189–194. https://doi.org/10.31887/DCNS.2020.22.2/mhilbert

Hilbert, M. (2020b, May 3). Social Media Distancing: An Opportunity to Debug our Relationship with our Algorithms. *Medium*. https://medium.com/@martinhilbert/social-media-distancing-an-opportunity-to-debug-our-relationship-with-our-algorithms-a64889c0b1fc

Hilbert, M. (2021). Information Theory for Human and Social Processes. *Entropy*, *23*(1), 9. https://doi.org/10.3390/e23010009

Hilbert, M., Ahmed, S., Cho, J., Liu, B., & Luu, J. (2018). Communicating with Algorithms: A Transfer Entropy Analysis of Emotions-based Escapes from Online Echo Chambers. *Communication Methods and Measures*, *12*(4), 260–275. https://doi.org/10.1080/19312458.2018.1479843

Hilbert, M., Barnett, G., Blumenstock, J., Contractor, N., Diesner, J., Frey, S., González-Bailón, S., Lamberson, P. J., Pan, J., Peng, T.-Q., Shen, C. (Cindy), Smaldino, P. E., Atteveldt, W. van, Waldherr, A., Zhang, J., & Zhu, J. J. H. (2019). Computational Communication Science: A Methodological Catalyzer for a Maturing Discipline. *International Journal of Communication*, *13*(0), 23.

Hilbert, M., & Darmon, D. (2020a). Largescale Communication Is More Complex and Unpredictable with Automated Bots. *Journal of Communication*, *70*(5).

Hilbert, M., & Darmon, D. (2020b). How Complexity and Uncertainty Grew with Algorithmic Trading. *Entropy*, *22*(5), 499. https://doi.org/10.3390/e22050499

Hilbert, M., James, R. G., Gil-Lopez, T., Jiang, K., & Zhou, Y. (2018). The Complementary Importance of Static Structure and Temporal Dynamics in Teamwork Communication. *Human Communication Research*, *44*(4), 427–448. https://doi.org/10.1093/hcr/hqy008

Hilbert, M., Liu, B., Luu, J., & Fishbein, J. (2019). Behavioral Experiments With Social Algorithms: An Information Theoretic Approach to Input–Output Conversions. *Communication Methods and Measures*, *0*(0), 1–20. https://doi.org/10.1080/19312458.2019.1620712

Hilbert, M., & López, P. (2011). The World's Technological Capacity to Store, Communicate, and Compute Information. *Science*, *332*(6025), 60–65. https://doi.org/10.1126/science.1200970

Jacobs, R. F., & Weston, F. C. (2007). Enterprise resource planning (ERP)—A brief history. *Journal of Operations Management*, *25*(2), 357–363. https://doi.org/10.1016/j.jom.2006.11.005

James, R. G., Ellison, C. J., & Crutchfield, J. P. (2011). Anatomy of a bit: Information in a time series observation. *Chaos: An Interdisciplinary Journal of Nonlinear Science*, *21*(3), 037109. https://doi.org/10.1063/1.3637494

James, R. G., Emenheiser, J., & Crutchfield, J. P. (2019). Unique Information and Secret Key Agreement. *Entropy*, *21*(1), 12. https://doi.org/10.3390/e21010012

Kelly, J. L. (1956). A new interpretation of information rate. *Bell System Technical Journal*, *35*(4), 917–926.

Kleene, S. C. (1967). *Mathematical Logic*. Courier Corporation. https://archive.org/details/KleeneMathematicalLogic/Kleene-MathematicalLogic/page/n233/mode/2up

Kolmogorov, A. N. (1941). Interpolation und Extrapolation von stationären zufälligen Folgen. *Bulletin Ofthe Academy of Sciences of the USSR*, *Series on Mathematics*(5), 3–14.

Kolmogorov, A. N. (1959). Entropy per unit time as a metric invariant of automorphisms. *Dokl. Akad. Nauk SSSR.*, *124*(4), 754–755.

Kolmogorov, A. N. (1963). On Tables of Random Numbers. *Sankhyā: The Indian Journal of Statistics, Series A*, *25*(4), 369–376.

Kolmogorov, A. N. (1968). Three approaches to the quantitative definition of information. *International Journal of Computer Mathematics*, *2*(1–4), 157–168. https://doi.org/10.1080/00207166808803030

Kondratieff, N. D. (1935). The Long Waves in Economic Life. *The Review of Economics and Statistics*, *17*(6), 105–115. https://doi.org/10.2307/1928486

Kuhn, T. S. (1962). *The Structure of Scientific Revolutions* (1st edition). University of Chicago Press.

Lanier, J. (2018). *Ten Arguments for Deleting Your Social Media Accounts Right Now*. Henry Holt and Company.

Lazer, D. (2015). The rise of the social algorithm. *Science*, *348*(6239), 1090–1091. https://doi.org/10.1126/science.aab1422

Lazer, D., Baum, M. A., Benkler, Y., Berinsky, A. J., Greenhill, K. M., Menczer, F., Metzger, M. J., Nyhan, B., Pennycook, G., Rothschild, D., Schudson, M., Sloman, S. A., Sunstein, C. R., Thorson, E. A., Watts, D. J., & Zittrain, J. L. (2018). The science of fake news. *Science*, *359*(6380), 1094–1096. https://doi.org/10.1126/science.aao2998

Lazer, D., Pentland, A., Adamic, L., Aral, S., Barabási, A.-L., Brewer, D., Christakis, N., Contractor, N., Fowler, J., Gutmann, M., Jebara, T., King, G., Macy, M., Roy, D., & Alstyne, M. V. (2009). Computational Social Science. *Science*, *323*(5915), 721–723. https://doi.org/10.1126/science.1167742

Lessig, L. (2000, January 1). Code Is Law. *Harvard Magazine*. https://www.harvardmagazine.com/2000/01/code-is-law-html

Lessig, L. (2006). *Code: And Other Laws of Cyberspace, Version 2.0*. Basic Books.

Leung-Yan-Cheong, S., & Cover, T. (1978). Some equivalences between Shannon entropy and Kolmogorov complexity. *Information Theory, IEEE Transactions On*, *24*(3), 331–338.

Levinson, M., Hutton, J., Ivey, J., & Brewster, K. (2020, June 26). *The Bit Player* [Documentary, Biography]. Institute of Electrical and Electronics Engineers (IEEE). https://thebitplayer.com/

Li, M., & Vitanyi, P. (1997). *An Introduction to Kolmogorov Complexity and Its Applications* (2nd ed.). Springer.

Lizier, J. T., Bertschinger, N., Jost, J., & Wibral, M. (2018). Information Decomposition of Target Effects from Multi-Source Interactions: Perspectives on Previous, Current and Future Work. *Entropy*, *20*(4), 307. https://doi.org/10.3390/e20040307

MacKay, D. J. C. (2003). *Information Theory, Inference and Learning Algorithms* (1 edition). Cambridge University Press.

MacKay, D. J. C. (2012). *Video lectures: Information Theory, Pattern Recognition, and Neural Networks*. University of Cambridge. www.inference.org.uk/mackay/itprnn/Videos.shtml

Markov, A. A., & Nagorny, N. M. (1988). *The Theory of Algorithms: Vol. translated by M. Greendlinger*. Springer. https://link.springer.com/book/9789027727732

Mayer-Schönberger, V., & Cukier, K. (2013). *Big data: A revolution that will transform how we live, work and think*. John Murray.

McAfee, A., & Brynjolfsson, E. (2012). Big Data: The Management Revolution. *Harvard Business Review*, *October*. http://hbr.org/2012/10/big-data-the-management-revolution/ar

McElreath, R., & Boyd, R. (2007). *Mathematical Models of Social Evolution: A Guide for the Perplexed*. University Of Chicago Press.

Mentzer, J. T., DeWitt, W., Keebler, J. S., Min, S., Nix, N. W., Smith, C. D., & Zacharia, Z. G. (2001). Defining Supply Chain Management. *Journal of Business Logistics*, *22*(2), 1–25. https://doi.org/10.1002/j.2158-1592.2001.tb00001.x

Mitchell, M. (2011). *Complexity: A Guided Tour*. Oxford University Press, USA.

Nahai, N. (2013). *Webs of Influence: The Psychology of Online Persuasion* (1st ed.). FT Press.

Nelson, R. R., & Winter, S. G. (1985). *An Evolutionary Theory of Economic Change*. Belknap Press of Harvard University Press.

Newborn, M. (2012). *Kasparov versus Deep Blue: Computer Chess Comes of Age*. Springer Science & Business Media.

Nodder, C. (2013). *Evil by Design: Interaction Design to Lead Us into Temptation*. John Wiley & Sons.

Orlowski, J. (2020). *The Social Dilemma* [Documentary]. Netflix. https://www.netflix.com/title/81254224

Pariser, E. (2011). *The Filter Bubble: What the Internet Is Hiding from You*. Penguin.

Pasquale, F. (2015). *The Black Box Society: The Secret Algorithms That Control Money and Information*. Harvard University Press.

Pentland, A., Choudhury, T., Eagle, N., & Singh, P. (2005). Human dynamics: Computation for organizations. *Pattern Recognition Letters*, *26*(4), 503–511. https://doi.org/10.1016/j.patrec.2004.08.012

Perez, C. (1983). Structural change and assimilation of new technologies in the economic and social systems. *Futures*, *15*(5), 357–375.

Perez, C. (2004). Technological Revolutions, Paradigm Shifts and Socio-Institutional Change. In E. Reinert (Ed.), *Globalization, Economic Development and Inequality: An alternative Perspective* (pp. 217–242). Edward Elgar. http://www.carlotaperez.org/papers/basic-technologicalrevolutionsparadigm.htm

Perez, C. (2015). From Long Waves to Great Surges. *European Journal of Economic and Social Systems*, *27*(1–2), 70–80.

Pierce, J. R. (1980). *An Introduction to Information Theory: Symbols, Signals and Noise* (2nd Revised ed. (1st 1961)). Dover Publications.

Plattform Industrie 4.0. (2018). *RAMI 4.0 – Ein Orientierungsrahmen für die Digitalisierung*. https://www.plattform-i40.de/IP/Navigation/EN/Home/home.html

Rahwan, I., Cebrian, M., Obradovich, N., Bongard, J., Bonnefon, J.-F., Breazeal, C., Crandall, J. W., Christakis, N. A., Couzin, I. D., Jackson, M. O., Jennings, N. R., Kamar, E., Kloumann, I. M., Larochelle, H., Lazer, D., McElreath, R., Mislove, A., Parkes, D. C., Pentland, A., … Wellman, M. (2019). Machine behaviour. *Nature*, *568*(7753), 477. https://doi.org/10.1038/s41586-019-1138-y

Richerson, P. J., & Boyd, R. (2004). *Not By Genes Alone: How Culture Transformed Human Evolution* (1st ed.). University Of Chicago Press.

Rissanen, J. (1978). Modeling By Shortest Data Description. *Automatica*, *14*, 465–471.

Rissanen, J. (2010). *Information and Complexity in Statistical Modeling* (Softcover reprint of hardcover 1st ed. 2007). Springer.

Rivoire, O. (2015). Informations in Models of Evolutionary Dynamics. *Journal of Statistical Physics*, *162*(5), 1324–1352. https://doi.org/10.1007/s10955-015-1381-z

Rivoire, O., & Leibler, S. (2011). The Value of Information for Populations in Varying Environments. *Journal of Statistical Physics*, *142*(6), 1124–1166. https://doi.org/10.1007/s10955-011-0166-2

Roberts, S. (2016, April 30). Claude Shannon, the father of the information age, turns 100. *The New Yorker*. https://www.newyorker.com/tech/annals-of-technology/claude-shannon-the-father-of-the-information-age-turns-1100100

Schreiber, T. (2000). Measuring Information Transfer. *Physical Review Letters*, *85*(2), 461–464. https://doi.org/10.1103/PhysRevLett.85.461

Schumpeter, J. A. (1939). *Business Cycles: A Theoretical, Historical, And Statistical Analysis of the Capitalist Process*. McGraw-Hill. http://classiques.uqac.ca/classiques/Schumpeter_joseph/business_cycles/schumpeter_business_cycles.pdf

Shalizi, C. R., & Crutchfield, J. P. (2001). Computational Mechanics: Pattern and Prediction, Structure and Simplicity. *Journal of Statistical Physics*, *104*(3–4), 817–879. https://doi.org/10.1023/A:1010388907793

Shannon, C. E. (1938). A symbolic analysis of relay and switching circuits. *Transactions of the American Institute of Electrical Engineers*, *57*(12), 713–723. https://doi.org/10.1109/T-AIEE.1938.5057767

Shannon, C. E. (1948). A Mathematical Theory of Communication. *Bell System Technical Journal*, *27*, 379–423, 623–656. https://doi.org/10.1145/584091.584093

Shannon, C. E. (1950). XXII. Programming a computer for playing chess. *The London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science*, *41*(314), 256–275.

Shapiro, C., & Varian, H. R. (1998). *Information Rules: A Strategic Guide to the Network Economy* (1st ed.). Harvard Business Press.

Sinai, Y. G. (1959). On the notion of entropy of dynamical systems. *Doklady Akademii Nauk*, *124*(4), 768–771.

Sisinni, E., Saifullah, A., Han, S., Jennehag, U., & Gidlund, M. (2018). Industrial Internet of Things: Challenges, Opportunities, and Directions. *IEEE Transactions on Industrial Informatics*, *14*(11), 4724–4734. https://doi.org/10.1109/TII.2018.2852491

Solomonoff, R. J. (1964). A formal theory of inductive inference. Part I and Part II. *Information and Control*, *7*(1,2), 1–22, 224–254. https://doi.org/10.1016/S0019-9958(64)90223-2

Striphas, T. (2015). Algorithmic culture. *European Journal of Cultural Studies*, *18*(4–5), 395–412. https://doi.org/10.1177/1367549415577392

Tsvetkova, M., García-Gavilanes, R., Floridi, L., & Yasseri, T. (2017). Even good bots fight: The case of Wikipedia. *PLOS ONE*, 12(2), e0171774. https://doi.org/10.1371/journal.pone.0171774

Turkle, S. (1984). *The Second Self: Computers and the Human Spirit*. Simon and Schuster.

Turkle, S. (1995). *Life on the Screen: Identity in the Age of the Internet*. Simon & Schuster.

Tutt, A. (2016). *An FDA for Algorithms* (SSRN Scholarly Paper ID 2747994). Social Science Research Network. https://papers.ssrn.com/abstract=2747994

Ver Steeg, G., & Galstyan, A. (2012). Information Transfer in Social Media. *Proceedings of the 21st International Conference on World Wide Web*, 509–518. https://doi.org/10.1145/2187836.2187906

Wagner, C., Strohmaier, M., Olteanu, A., Kıcıman, E., Contractor, N., & Eliassi-Rad, T. (2021). Measuring algorithmically infused societies. *Nature*, *595*(7866), 197–204. https://doi.org/10.1038/s41586-021-03666-1

Wang, Y., & Kosinski, M. (2018). Deep neural networks are more accurate than humans at detecting sexual orientation from facial images. *Journal of Personality and Social Psychology*, *114*(2), 246–257. https://doi.org/10.1037/pspa0000098

Watts, D. J. (2007, January 31). *A twenty-first century science* [Comments and Opinion]. Nature. https://doi.org/10.1038/445489a

Williams, P. L., & Beer, R. D. (2010). Nonnegative Decomposition of Multivariate Information. *ArXiv:1004.2515 [Math-Ph, Physics:Physics, q-Bio]*. http://arxiv.org/abs/1004.2515

Winter, S. (1964). *Economic "Natural Selection" and the Theory of the Firm* (pp. 225–272) [LEM Chapters Series]. Laboratory of Economics and Management (LEM), Sant'Anna School of Advanced Studies, Pisa, Italy. http://econpapers.repec.org/bookchap/ssalemchs/winter-1964.htm

Wu, Y., Kosinski, M., & Stillwell, D. (2015). Computer-based personality judgments are more accurate than those made by humans. *Proceedings of the National Academy of Sciences*, 201418680. https://doi.org/10.1073/pnas.1418680112

Zuboff, S. (2019). *The Age of Surveillance Capitalism: The Fight for a Human Future at the New Frontier of Power*. PublicAffairs.

Zurek, W. H. (1989). Algorithmic randomness and physical entropy. *Physical Review A*, *40*(8), 4731. https://doi.org/10.1103/PhysRevA.40.4731