Digitizing as a Driver of Sustainable Economy, Health and Environment

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Edited by

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PREFACE: DIGITIZING AS A DRIVER TO SUSTAINABLE ECONOMY, HEALTH AND ENVIRONMENT

RAUNO RUSKO AND VILLE PIETILÄINEN

1. General perspectives of digitizing

Digitizing is one of the most critical disruptions in the contemporary social and business environment. Several studies see digitizing (digitalization) as a contemporary industrial revolution (Rusko & Kosonen, 2023). It has several technological forms, such as electronics, the Internet, Information Technology (IT), automated production, cyber-physical systems, and cybernetics (Rusko & Kosonen, 2023). It has effects on each part of everyday life. Furthermore, digitizing has various forms suitable as tools for sustainable business, health, and the environment. Generally, digitizing has the following effects, for example: the development of human capital in the population, digital technology access in households permits participation in e-commerce, integration of digital technology by small and medium enterprises (SMEs), and digitizing of public services (Au, 2024). Furthermore, Au (2024) finds these effects as the drivers of income inequity. However, digitizing may be the driver of sustainability, a sustainable economy, health, and environmental improvement. This book focuses on these forms and the effects of digitizing. Digital environmentalism, for example, can defend against climate change (Bakker, 2024).

Corporate digital responsibility is one of the concepts that cover relatively widely these positive effects of digitizing (see, e.g., Dörr, 2021; Wilkinson, 2023). According to Dörr (2021), corporate responsibility is changing due to the age of big data and artificial intelligence towards corporate digital responsibility, which offers companies a sustainable competitive advantage. Wilkinson (2023) considers that corporate digital responsibility refers to responsible action in all areas related to digitalization. Parallel to the perspectives of Au (2024), Wilkinson (2023) and Lobschat and colleagues

(2021) express with corporate digital responsibility various opportunities and threats of digitizing, such as ethical dilemmas related to digitizing.

Digitizing as a driver of sustainable environment

Sustainable development was an important theme in the Brundtland report (Kivivirta, Laakkonen, Leinonen and Liljeroos-Cork, 2025), which started various sustainability discussions, such as sustainable business (Beehner & Beehner, 2019), green business (model) (Solesvik, Torgersen, Andersson & Valter, 2022), depleting natural resources (Meadows, Meadows, Randers & Behrens_III, 1972) and even degrowth discussions (Kallis et al., 2018). Sustainable business has several meanings and definitions and is often introduced with "green business" (Solesvik et al., 2022). According to Solesvik and colleagues (2022), the green business model has several resembling concepts, such as a sustainable business model, Greentech business model, triple bottom line business model, circular business model, and various renewable energy business models. The role of digital tools, digitizing, and technology are important in each of these forms of business models. Greentech business model, for example, is defined as: "…an integrative approach that combines two well-established concepts in the academic literature for categorization of Greentech business models, specifically business model archetype and technological entrepreneurship activities" (Trapp & Kanbach, 2021, p. 5; see also Solesvik et al., 2022). Also, contemporary circular economy business is based on various forms of Artificial Intelligence (AI) and digitizing (Rusko, 2024).

Digitizing as a driver of sustainable business and economy

Traditionally, sustainable business is understood and linked with concepts such as business ethics and Corporate Social Responsibility (CSR). These concepts and themes are important today but have been completed by broader, more accurate themes and even measurable platforms. Digitizing is an eligible tool to establish systems and platforms for sustainable business. Typically, several global systems and sets of sustainable business platforms, such as ESG (Environment, Social, and Governance), SDGs (Sustainable Development Goals) of the United Nations, and GRI (Global Reporting Initiative), lean on vast digital information systems and evaluation. Furthermore, the European Union (EU) has established its systems and legislation for sustainable business and economy.

Information, implementation, and control of many directives on sustainable business in the EU, for example, are based on digital tools and platforms. One example is CSRD (Corporate Sustainability Reporting Directive) reporting, which follows ESRS (European Sustainability Reporting Standards) and uses certain digital programs (XBRL) to provide transparency in sustainability reporting.

However, it is important to understand that sustainable business needs real activities and actual values. Digitizing is not only a channel to inform and measure these activities, but it may also be a tool to develop sustainable business and business ethics. Sustainable supply chain management (SSCM), for example, exploits digitizing to enhance the use of materials in the supply chain (Pham et al., 2024).

Digitizing as a driver of health

Digitalization drastically transforms both the healthcare structures and the idea of health. Intertwining technology with health promotion (eHealth) has taken research steps since the beginning of the millennium, representing a novel turn in health studies (Granja et al., 2018). Regarding the structures, the emphasis is shifting from the physical healthcare buildings to closing the patients. New roles for technology and humans are also emerging in health care (Pietiläinen, Saari & Rusko, 2025, in press). In particular, the development of digital twins, a concept that focuses on technological replicas of real-world physical objects (Hu et al., 2021) and exploits statistical data and probabilistic simulations in the modeling (Rios et al., 2015), shapes patient treatment, health care professionals training, pharmaceutical industry, and the management practices associated with healthcare (De Benedictis et al., 2023).

Examples of patient treatment incorporate predictive, preventive, personalized, and participative medicine practices. The objective is to treat patients individually, transforming the familiar medical instruments and software from hospitals to work, home, and school (De Benedictis et al., 2023). Regarding healthcare professional training, real-time replicas of the patients can be used in surgical practice and the robotic system for surgeons (Hagmann et al., 2021). Digital twins are also used in pharmaceutical production, smart manufacturing, and drug discovery (De Benedictis et al., 2023). Here, the role of digital twins is crucial in data management, that is, in integrated information from various scientific and clinical sources (Subramanian, 2020).

The trajectories around the digital twins incorporate significant potential for technological innovations and economic growth but also many functional and ethical challenges. The fundamental question in the background of technological development is how we perceive the role of humans and technology. Moreover, perhaps more essential questions are whether we are aware of the changes in the roles, their effects on humans, and how much we are ready to accept changes in these roles.

2. Combining the three aspects

This book is not only about how digitizing serves as a driver to a sustainable economy, health, and environment. Moreover, the objective is to combine these three aspects. In a complex world, it is not always realistic to simultaneously reach economic, environmental, and social needs. Consequently, it is essential to consider the criteria for the aspects and, more generally, define what economic, environmental, and social objectives we aim for in digitalization. This defining task is not only practical but also conceptual and philosophical.

In etymology, technology has played the role of an object, a tool, or equipment a human can instrumentally use. This conventional concept has been drastically challenged as fast evolving, at least partially opaque algorithms shape people's experiences and, ultimately, the actions they commit in the real world. In organization studies highlighting the process perspective, the role of technology with an agency has been recognized for years (Orlikowski, 2007). However, ontological statements do not necessarily achieve practical decisions as technology contains material value for the economy and services.

From a process ontological perspective, in a complex world, people live in the middle of disturbances mediated by technology. Consequently, technology shapes human experiences and behavior as people process and search for solutions to disturbances (Barker, 2023). Following this logic, technology contains the role of a 'quasi-object' (Serres, 2007) instead of a subject or an object. Technology, like a ball in a game, does not work independently without commands or the initiator but is inextricably linked to the functioning of the digital society. From that perspective, it can be considered crucial to understand how technology shapes the human world.

The book does not address a process perspective as the only conceptual framework for considering digitalization in a society. However, we want to highlight that there are different ways of investigating technology beyond the instrumental perspective that dominates the public debate and decision-making. This book welcomes these different perspectives.

3. About the content of the book

This book aims to provide a topical overview of the role of digitization in contemporary society's everyday life. Digitizing is an important feature and driver in health control, entrepreneurship and start-ups, and environment protection, among other things. Furthermore, sustainability is another spreading feature in contemporary life. The chapters of the book will mostly combine digitizing and sustainability in various forms.

Due to topical themes and their combinations, this book and its chapters provide valuable and interesting viewpoints on the field of social science and its connections with digitizing and sustainability.

Methodology is mainly based on qualitative methods and case studies, but some chapters use quantitative methods to complete the analysis. Theoretical analysis, which is linked with the book's themes, is one research design option. Furthermore, the authors have extensive experience with the themes of this book, which is apparent in the content and quality of the chapters. In addition, these professional experiences often complete the book chapters' analysis and methodology.

Laakkonen and Kivivirta introduce ontological perspectives of digitizing in Chapter 1**.** They study what it means to understand AI as “ontological assumption” in relation to Habermas’s ontological assumptions of information, spacetime, interest of knowledge and organizing. Mostly philosophical nature of AI and the background assumptions of modelling AI algorithms are little noticed themes in the literature, but this especially chapter focuses on these themes.

Chapter 2 focuses on the roadmap towards sustainable use of predictive AI in public administration. Kivivirta, Laakkonen, Leinonen and Liljeroos-Cork utilize Soft System Methodology (SSM) as a tool to build the elements of a roadmap to sustainable use of predictive AI in public administration. According to them, the utilization of AI lacks a consistent, systematic approach and reliable information on the effectiveness of the AI utilization on the public administration management and decision-making is incomplete.

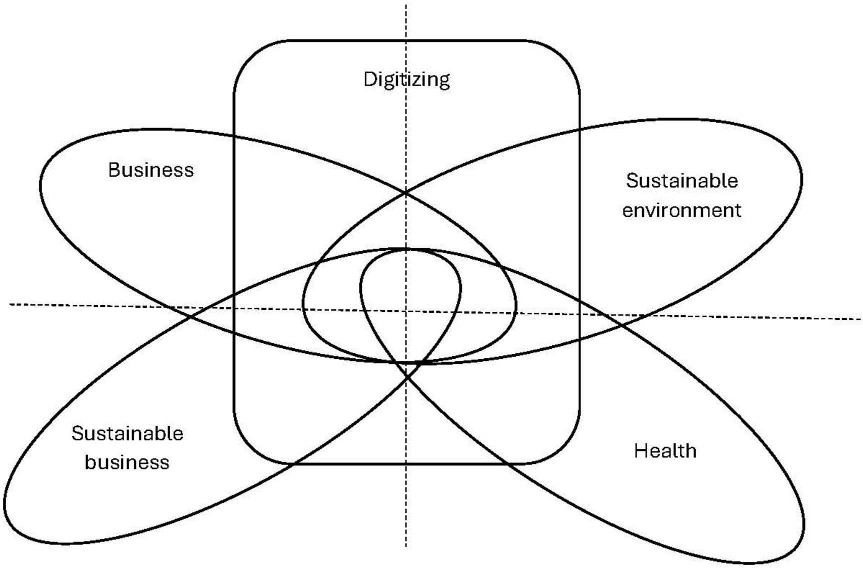

Figure 1. Themes of the book.

In Chapter 3, Pietiläinen, Kangasniemi and Rusko investigate the role and use of technology in managing well-being at work with a case study targeted to one branch of industry. They approach technology from an experiential perspective, analyzing the different roles of technology, highlighted in a postphenomenological research tradition. The chapter opens avenues for experiential technology research and practical well-being technology development in the context of work.

In Chapter 4, Kangasniemi and Pietiläinen further develop the experiential approach by adopting a sensemaking and digital employee experience (DEX) view of technology. These perspectives contradict the various roles of technology, placing the employees in the middle of the different requirements and solutions. This chapter also contributes to experiential technology research.

In chapter 5 Rusko and Pantsar introduce some problems of digital marketing, and especially among videos. Companies provide numerous marketing videos to digital platforms, which do not meet customers and their interest. However, ambitious value-based (strategic) videos, such as in the case of Gillette, draw attention but mainly negative ones among customers. This chapter creates the concept of “paradox of videos”.

Lindholm and Rusko consider in chapter 6 four Finnish startups, which are technically developed: Wolt, Supercell, OURA and Spinnova. All these firms are established during the era of “post-Nokia”, established after some kind of collapse of Nokia. Chapter Y focuses on sustainability, grand challenges and SDGs (Sustainable Development Goals) of the United Nations. All these four firms have responsible activities, but especially Spinnova.

Chapter 7 focus on digital entrepreneurial ecosystems in rural Northern Finland. In this chapter Katja Lindholm continues to study the digitizing of entrepreneurship. Outcomes are based on the comments of local (and municipal) business advisers and the Author’s own wide field experiences. Digital infrastructure governance (DIG) and business advisers have an important role in fostering entrepreneurship by addressing local barriers and supporting digital growth.

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CHAPTER ONE

ARTIFICIAL INTELLIGENCE ULTIMATE NATURE OF BEING: THE BACKGROUND ASSUMPTIONS OF MODELLING AI ALGORITHMS

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Abstract

While there is much discussion today about technological and mathematical models of artificial intelligence (AI), less work has been done on the philosophical nature of AI and the background assumptions of modeling AI algorithms. This chapter explores what it means to understand AI as an "ontological assumption" about

Habermas's ontological assumptions of information, interest in knowledge, organizing and spacetime. Distinguishing how four AI paradigms and Habermas's ontological assumptions are related, this chapter focuses on AI's "ontological" roles in our society. It argues that Habermas' ontological assumptions show how AI paradigms reorganize our society and future in particular societally significant ways.

Keywords: *Habermas, AI paradigms, Ontology, Knowledge Interest, Modeling paradigms, Spacetime*

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Introduction

In this chapter, we focus on the background assumptions of model Artificial Intelligence (AI) algorithms, focusing on the interest of knowledge, ontology of organizing, and space-time. Why have we chosen the interest of knowledge, the ontology of organizing, and space-time as the subject of consideration? Because the organization of information is essential in building data structures for all AI paradigms. Although different AI paradigms use different data representation models (e.g., symbolic logic, neural networks, probabilistic models), all AI parameters require structured data. AI systems learn from data, which is organized information. The data structure affects the learning process and the resulting model, whether supervised, unsupervised, or reinforcement learning. The organization of information affects the efficiency and accuracy of reasoning processes. Understanding how AI systems make inferences often requires analyzing the organization of the system's information. AI systems seek to interact with the physical world, which requires understanding space and time. Robotics, autonomous vehicles, and virtual reality are good examples. AI tasks involve thinking about events and their temporal relationships. For example, planning, scheduling, and forecasting require understanding temporal concepts. Tasks such as image recognition, natural language processing, and geographic information systems rely on spatial reasoning, which requires a representation of space. Understanding causal relationships often requires taking spatial and temporal factors into account. Many state-of-the-art AI systems aim to discover or model causal relationships.

The interaction between the organization of information and time-space ontologies can be seen particularly clearly in all AI paradigms and AI models. These structures combine information representation with location and time information, which enables complex reasoning tasks. For example, spatiotemporal data mining and extracting meaningful patterns from data includes spatial and temporal dimensions and requires advanced data organization techniques. Both information organization and spatiotemporal ontologies are essential components of any AI system, regardless of its paradigm. They provide the basic structures for representing processing and reasoning about the world, making them essential in developing intelligent systems. Finally, information organization and spatiotemporal ontologies are essential components of any AI system, regardless of its paradigm. They provide the basic structures for representing, processing, and reasoning about the world, making them essential in developing intelligent systems.

We do not discuss the history of AI from the beginning, starting from Alan Turing (Turing, 1950) and the birth of intelligent machines from the well-known problem of decidability in arithmetic to understand how AI has emerged, its context and motivation behind it, the classes of approaches studied to reach AI from its birth up to now and their evolution. Instead, we seek to enlighten how the main paradigms for modeling artificial intelligence are based on different scientific traditions, which see the world from different perspectives and have different knowledge interests. Here, we define the term "knowledge interest" as a paradigm of modeling algorithms that treats and approaches the production of new conceptual and practical knowledge. It is related to the philosophical term Erkenntnisinteresse coined by German social theorist Jürgen Habermas (1970; 1978). This Habermasian concept has profoundly affected the characterization of scientific disciplines, helping to characterize the ways of approaching any scientific paradigm and discipline. In his work, Habermas considered that natural sciences are empirical–analytical sciences aiming to control through prediction while understanding and emancipation characterize humanities and social sciences.

AI lives in our infosphere (Floridi, 2014a) and is part of our reality. It is increasingly embedded in, even determining, our everyday lives (Bones et al., 2021; Shakir, Png & Isaac, 2020). So far, we have been proceeding as if we have a firm and precise grasp of the nature of AI. Philosophers know better than anyone that precisely defining a particular discipline to the satisfaction of all relevant parties, including those working in the discipline itself, can be acutely challenging. (Bringsjord & Govindarajulu, 2018). However, philosophers still consider what is the ultimate essence of AI. The question is tricky, maybe even eternally unanswerable, especially if the target is a consensus definition. In this paper, we propose ontological assumptions about AI. The paper opens a wider debate on the paradigmatic differences for modeling artificial intelligence algorithms. We have used the term "paradigm" rather freely as an indicative concept that forms a distinct field. The practical problem is that people who approach or are trained to model artificial intelligence algorithms from different sciences are often unaware of others' background assumptions. According to the Oxford English Dictionary, ontology is the philosophical study of reality and is concerned with the nature or essence of being or existence; essential existence" ("onto" existence or being real and "logia" science or study).

Here, we ask, what is the essential existence of AI in the background assumptions of modeling AI algorithms? What provides a definitive and exhaustive classification of entities in all spheres of being? More specifically, what is an ontology in AI science? Now, the ontology of AI is knowledge represented formally: a hierarchy of concepts within a domain, a shared vocabulary to denote the types, properties, and interrelationships of those concepts. An ontology in AI is a specification of conceptualization and designed for reuse across multiple applications and implementations. In other words, the specification of conceptualizations is a written, formal description of a set of concepts and relationships in a domain of interest (Karp, 2000).

AI literature contains many definitions of ontology, which contradict one another (Karp, 2000). An ontology and a set of individual instances of classes constitute a knowledge base. There is a fine line where ontology ends and the knowledge base begins. Until now, an ontology of AI has only been the arrangement of different kinds of things into types and categories with a well-defined structure. To define ontology as a formal representation of the domain of knowledge. It is an abstract entity: it defines the vocabulary for a domain and the relations between concepts, but an ontology says nothing about how the knowledge is stored (as a physical file, in a database, or some other form) or, indeed, how the knowledge can be accessed. A knowledge base is a physical artifact: a database, a repository of information that can be accessed and manipulated in some predefined fashion. The top-level ontology or foundation ontology describes the most general concepts that are the same across all knowledge domains (e.g., entity). But it is simple: for AI model developers, the knowledge is in the database, and data structures are in the file. Different modes of thought and philosophical traditions have different ontological ways to view things.

Earlier philosophers debated the importance of epistemic values, such as internal consistency, falsifiability, the generalizability of particular theories, and notions of scientific objectivity. Values shape the veracity of scientific statements, aiming to establish broader ontological or causal claims about the nature of AI systems. (Laudan, 1968; Bueter, 2015). Habermas's ontological assumptions elaborate Adam's (1995) epistemological questions related to AI. Her (1995) view is that traditional epistemological assumptions of AI focus too narrowly on modeling intelligent human behavior (see. Luger & Stubblefield, 1993) and ignore power relations in wider society. She brings up the epistemology questions "how AI systems are used to represent knowledge, what kind of knowledge and whose knowledge they contain." In addition, from traditional paradigmatic views of AI, the question remains: how to model humans' unique ontological mode of existence (Søraker, 2014)?

In this chapter, we address the following research question: What is the ultimate essence of artificial intelligence, focusing on the interest of knowledge, ontology of organizing, and modeling space-time as the subject of consideration? In order to improve our critical understanding of the conceptual nature and practical consequences of AI technologies, we provide the conceptual foundations for AI's ontological developments in four paradigms: 1) modeling neural networks, 2) modeling genetics, 3) modeling genealogy, and 4) modeling physical phenomena be able to elaborate our question, what is the ultimate essence of AI.

Habermas's ontological assumptions of four artificial intelligence modeling paradigms help us understand AI's phenomenological acts in our society. For example, when the artificial neural network predicts dense breast tissue, the pixels in a given mammogram that led to it being classified as dense may be simple enough to be understood by visual inspection, while what makes tissue dense might be too complex to understand. (Erasmus, Brunet & Fisher, 2020).

This paper's ontological discourse is grounded in "being" and "logical". In other words, what entities exist or may be said to exist, and how such entities may be grouped, related within a hierarchy, and subdivided according to similarities and differences. Based on our analysis, we can enlighten the philosophical foundations of AI and show the implications of distinct scientific traditions in the four main paradigms for modeling artificial intelligence algorithms, which consequently see the world from different perspectives.

The high-dimensional complexity makes many AI-programmed computing systems unpredictable, even with complete knowledge of the underlying parameter values. Moreover, there is often no way of knowing in advance whether intervention on a single parameter will change the relevant system's behavior entirely or else affect it in a way that is mostly or entirely imperceptible. (Zednik, 2021). The modeling of artificial intelligence algorithms is a highly complex task, and therefore, an interdisciplinary approach that combines concepts and methods from these four different paradigms might help to give insights into developing the future of AI better.

We need a more profound understanding of the ontological nature of AI, i.e., its ultimate essence of being, why artificial intelligence works as it works in our society, and how it can be developed sustainably for social goods. Why have we chosen the ontology of interest of knowledge, organization, and space-time as the subject of consideration? The philosophical starting point of social science and creating a social theory of AI is to look at the interest in knowledge and knowledge in terms based on Habermas's philosophy of science. The organization of knowledge and the ontologies of space-time are in the interest of all artificial intelligence paradigms and apply to all existing models of artificial intelligence that seek to understand the layered dynamics of the world (Guarino, 1998).

A paradigm shift can be seen towards nature-inspired self-organizing AI models inside the AI research community. (de Bézenac, Pajot & Gallinari, 2019). In those models, AI finds the solution to specific problems independently. AI developers specify basic architectural principles, such as whether the system is a deep neural network, a support vector machine, or a decision tree. Moreover, they specify an appropriate learning algorithm and select a suitable learning environment to attribute values to the system's learning parameters (e.g., the connection weights within an artificial neural network). AI developers do not set these values themselves. Instead, the learning algorithm sets the parameter values through its engagement with the learning environment. Thus, AI developers do not specify how an AI problem is solved but merely specify the conditions under which a solution may eventually be found. (Zednik, 2021). In many cases, rendering an opaque system transparent will not involve acquiring knowledge of parameter values. However, it will instead require knowledge of the environmental patterns and regularities being tracked and the abstract representational structures tracking them (Buckner, 2018). One starting point to elaborate on the essence of AI in our ecosystems is to identify epistemologically relevant elements that produce knowledge. (Zednik, 2021).

Currently, existing algorithmic modeling paradigms fail to consider phenomena outside the AI models, random variables (epistemologically relevant elements) are excluded, and prediction is difficult in dynamic contexts. In response to these limitations, a new nature-based AI modeling paradigm is expected to provide a path to the organic self-organizing and adaptive models of the future, where nature's own behavior is implemented into our technological world and toward a sustainable and socially sound theory of AI models. In this paper, we argue that the ultimate nature of AI can be found in nature, where AI is engaged with the learning environment, with a lack of influence.

The four paradigms

There is a long literature of philosophy, applied mathematics, and computer science, where AI is divided into three categories: a) Weak AI, which is programmed to perform a specific task only; b) Strong AI or Artificial General Intelligence (AGI), which can perform like a human or possess human-level intelligence and c) Super AI, which has its consciousness, and intentionality. (Ng & Leung 2020; Scerri & Grech 2020). Luciano Floridi (2019) states that AI paradigms still satisfy the classic definition provided by John McCarthy, Marvin Minsky, Nathaniel Rochester, and Claude Shannon, in their seminal "Proposal for the Dartmouth Summer Research Project on Artificial Intelligence," were the founding document and later event that established the new field of AI in 1955.

Corea (2018) divides the AI paradigms into symbolic (logic-based, knowledge-based), statistical (probabilistic, machine learning), and sub-symbolic (embodied intelligence, search and optimization) paradigms. A broad spectrum of artificial intelligence algorithms belongs to different classes of approaches (conservative/modern), including fuzzy logic, expert systems, evolutionary strategies, and genetic programming. (Russell & Norvig 1995). However, there are also differences between different paradigms in natural sciences. These differences mean there are different paradigmatic underpinnings for modeling artificial intelligence algorithms that determine the key assumptions of information, the ontology of organizing, and the ontology of modeling spacetime. For instance, formal logic requires a unique language free from ambiguities, much like a programming language ("if p then q") (Edwards, 1997).

To analyze the ontological foundations of modeling paradigms for artificial intelligence algorithms, we use the following classification: 1) paradigm that models neural networks, 2) paradigm that models genetics, 3) paradigm that models genealogy, and 4) paradigm that models physical phenomena. (Darwin & Huxley 2003; Fausett, 1994; Goldberg, 1998; Kramer, 2017 & Lee, 2019; Nie, Bo, Zhang & Zhang, 2020). Paradigms (2) and (3) are partially overlapping, and some view that (2) is, in fact, the most significant part of (3). However, we keep them distinct because of genealogy's significant role and its different paradigmatic assumptions. Modeling genetics is a biology-based science that purely investigates chromosomes without considering the population's adaptation to the environment. It is also worth noting that paradigm (4) is only slowly emerging and has not yet been fully institutionalized.

Nevertheless, we decided to include it here because of its distinctive features and future potential. In addition to assumptions of information and interest in knowledge, we decided to analyze the ontology of organizing and modeling spacetime because of the increasing practical use of these algorithms in organizing. Floridi (2021) emphasizes that the digital has been transforming (re-ontologising) the relationship between space and time by modifying a third variable: the speed of the processes of communication (both in the sense of interacting and in the sense of transferring) and manipulation (transforming) of something.

There is also relatively little AI philosophical research on algorithms focusing on temporal abstraction in time and space. One of the rare types of research by Paul Humphrey (2009) analyzes physics and molecular biology and states that AI agents are relative. In time, it concerns the (lack of) a certain kind of knowledge “a cognitive agent X at time t just in case X does not know at t all of the epistemically relevant elements of the system. (Humphreys, 2009). Also, Coeckelbergh’s paper is one of the few exceptions, which opens the philosophical discussion of AI about time, process, and narrative to conceptualize AI and its normatively related impact on human lives and society. (Coeckelbergh, 2021).

Indeed, like the computer systems being developed using AI, biological cognizes can be explained electrochemically (e.g., by reference to neurobiological mechanisms), mathematically (e.g., by reference to computational processes), and rationally (e.g., by reference to beliefs and desires, see, e.g., Dennett, 1987).

Staunchly, reductionist, or eliminative philosophical tendencies notwithstanding (e.g., Bickle, 2006; Churchland, 1981), all of these explanations are equally legitimate, and all EREs invoked in these explanations can be considered equally accurate. Next, we introduce the paradigms.

Modeling neural networks

Interest in neural networks began in the late 1940s, and this interest resulted in the birth of Perceptron (a computerized machine devised to simulate the ability of the brain to recognize and discriminate). Edmund Berkeley, for example, wrote Giant Brains, or Machines That Think (1949), to explain the "new machines" to the general reader.

Widespread AI applications began to emerge during the 1980s and were influenced by research in neuroscience. Today, this paradigm includes all AI algorithms grounded on deep neural networks and convolutional deep learning networks. Neural networks are a family of methods belonging to the machine learning approach (LeCun, Bengio & Hinton, 2015). As a notable example, the modeling neural network paradigm includes all the machine learning approaches, such as kernel methods. Classifier for discriminative vs. generative models is commonly used in machine learning techniques. The deep learning neural network models distinguish supervised learning models, unsupervised learning models, semi-supervised learning models, and self-supervised models. Deep-learning methods are representation-learning methods with multiple levels of representation, obtained by composing simple but non-linear modules that each transform the representation at one level (starting with the raw input) into a representation at a higher, slightly more abstract level. Representation learning is a set of methods that allows a machine to be fed raw data and automatically discover the representations needed for detection or classification. With the composition of enough such transformations, very complex functions can be learned. Learning is more than improving one's performance on particular tasks with experience; it is not confined to rational thinking. Learning is a more holistic activity linked to survival and involves our "neurobiological architecture" and senses that interact with the world. The neural networks only receive a vector of the features considered relevant to its task and do not have a wider context to learn from, nor any incentive to do so, as it is being measured only on performance on the one task. (Bones & al. 2021).

Interest of knowledge

Deep learning probabilistic algorithms perform calculation, data processing, and automated reasoning tasks. Many models for modeling predictive deep learning algorithms have their background in neuroscience, which assumes that the human brain neurons can be interpreted as a decentralized system where multiple tasks are handled simultaneously in neural networks. For instance, in deep learning, a convolutional neural network (CNN or ConvNet) is a class of deep neural networks most applied to analyzing visual imagery. The convolutional network layers map the function of the human visual systems, where the linear predictive models in several layers function simultaneously. This encoding model makes it possible to predict the topography of responses to any new stimulus using a network of neurons to predict the visual responses (Eickenberg, Gramfort, Varoquaux & Thirion, 2017; Cichy et al., 2016).

Assumptions of information

The basic models used in computer science to approach predictive deep learning algorithms are analogical and track thinking models. The idea behind these thinking models is that historical data repeatedly acts similarly. Therefore, the development of new algorithms is based on historical data. However, they are ahistorical from a socio-technological foresight point of view (Shakir, Png, Isaac, 2020) in a specifically limited framework. The main limitation of these models is that they only consider the historical time and dismiss the present and the future. AI and data science processes fix knowledge of the past (Coeckelbergh, 2021). The future of AI lies not just in historical big data, but also, or perhaps mainly, in its increasing ability to generate its data (Floridi, 2021).

Ontology of organizing

Multiple methods exist to identify and compare neuronal codes with deep-learning neural networks. In the adaptation method, there are multiple stimulus receptions, where after each stimulus, the predictiveness of responses increases and reaction time decreases. (López-Barroso et. al. 2020). Thus, the main goal of neuroscience is not to predict the future but to identify the artificial neural network that best mimics the visual cortex responses (Yaminsa et. al. 2014). All the neural network models are based on the idea of input and output, where interference occurs between the processes. The interference part is the predictive algorithm artificially optimized for desirable output.

Ontology of modeling spacetime

A recurrent neural network (RNN) is a class of artificial neural networks where connections between nodes form a directed graph along a temporal sequence. In mathematics, a sequence is an enumerated collection of objects in which repetitions are allowed, and order does matter. How LSTM exactly works is not entirely understood because the use of long- and short-term memory is important, but it is difficult to ascertain what time in the process they are needed. For example, the neural network architecture may require short-term memory at the end of the process and long-term at the beginning of the process. Indeed, learning, planning, and representing knowledge at multiple levels of temporal abstraction are longstanding challenges for AI. In their seminal paper, Sutton, Precup, and Singh (1999) consider how these challenges can be addressed within the mathematical framework of reinforcement learning and Markov decision processes (MDPs) and extend the usual notion of action in this framework to include options-closed-loop policies for acting over a period. Another option is to use the New Mechanic explanation to describe the collection of entities and activities. When the artificial neural network (ANN) is recurrent, the pathways can always be unrolled and mechanistically depicted. (Erastmus et al. 2021).

Modeling genetics

Interest of knowledge

Genetic algorithms are a family of computational models inspired by biology to model ecology based on biology and genetics. Often, genetic algorithms refer to a model introduced by John Holland (1975) and his students, such as DeJong. It is still a case that most of the existing and recent theories of genetic algorithms apply solely or primarily to the model introduced by Holland and variations on canonical generic algorithms (Vose, 1993). For instance, canonical generic algorithms can be based on binary strings, with crossover, mutation as variation operator, and fitness–proportionate selection. When implementing genetic algorithms to a *population* of chromosomes, one evaluates the structures and allocates reproductive opportunities so that those chromosomes that represent a better solution to the target problem are given more chances to reproduce than those with poorer solutions. Solutions' goodness is typically defined concerning the current population (Whitley, 1993).

Assumptions of information

In this paradigm, selection, crossover, and mutation of cells are viewed as the sources of information. Therefore, all genetic algorithms encode a potential solution to a specific problem as a simple chromosome like a data structure and then apply recombination operations to these structures to preserve critical information. The improvement in the main components of this algorithm (selection, crossover, and mutation) is the most fundamental for modeling genetics. Several trends are evident in recent theoretical work. First, most researchers continue to work with minor variations on Holland's (1975) canonical genetic algorithm because this model continues to be the easiest to characterize from an analytical viewpoint. Second, Markov models have become more common as tools for providing supporting mathematical calculations.

Ontology of organizing

In a broader term, a genetic algorithm is any population-based model that uses selections and recombination operations to generate new sample points in a search space. Therefore, there are complex interactions among their parameters. Many genetic algorithm models have been introduced by researchers, essentially working from an experimental perspective. Many of these researchers are application-oriented and are typically interested in genetic algorithms as optimization tools (Whitley, 1993). The AI knowledge map presented by Corea (2018) places genetic algorithms' problem domains so that genetic algorithms can also be used for planning and communication purposes in the context of the ontology of organizing.

Ontology of modeling spacetime

Genetic algorithms use multi-dimensional and stochastic search methods involving complex interactions among their parameters in the search for space. For the last two decades, researchers have been trying to understand the mechanics of parameter interactions by using various techniques. These methods include careful functional decomposition of parameter interactions, empirical studies, and Markov chain analysis. With such analysis, the values of parameters (such as population size, choice of operators, operator probabilities, and others) to use in an arbitrary problem have long remained an open question (Kalyanmoy & Agrawal, 1998). In the end, what is striking about genetic algorithms and the various parallel models is the richness of their computation and the ways simple algorithm changes often result in surprising emergent behavior.

Modeling genealogy

Interest of knowledge

The paradigm for modeling the theory of evolution based on genealogical data produces evolutionary algorithms equipped with several random (stochastic) components, which select and combine solutions in each population. They model the theory of evolution based on genealogical data. This makes them unreliable in finding similar solutions in each run as opposed to deterministic algorithms. Deterministic algorithms (e.g., brute force search) find the exact solution in every run but suffer from slower speed and local solution stagnation when applied to large-scale problems (Mirjalili et al., 2019).

Assumptions of information

One of the fastest-growing sub-fields of computational intelligence is evolutionary computation. In this field, many algorithms solve optimization problems. These algorithms mimic and simulate the Darwinian theory of survival of the fittest (Reynolds, 1987). Such algorithms mostly mimic biological evolution in nature (Mirjalili et. al. 2019). In other words, they use genealogical information about population adaptation to the environment. This means that evolutionary algorithms (EA) only search a part of the search space using heuristic information instead of population adaptation.

Ontology of organizing

EAs that model genealogy is stochastic and mostly heuristics. Finding the best solutions in each population to survive and using them to improve other solutions allows these algorithms to search promising regions of the search space. The wide range of large-scale applications of EAs has been well-established and shows such techniques' continuing popularity and flexibility in organizing (Mirjalili et. al., 2019). For example, Srinivas & Patnaik

(1993a, 1993b) extends models that appear to look at binomially distributed populations. Suzuki (1993) used Markov chain analysis to explore the effects of elitism (where the individual with the highest fitness is preserved in the next generation). Qi & Palmieri (1994) utilized infinite population models of genetic algorithms to study selection and mutation and the diversification role of crossover, while Rudolph (1994) focused on the convergence behavior of canonical genetic algorithms.

Ontology of modeling spacetime

In predictive deep learning algorithms, where selections are made in multiple possibilities, the essential concept is selection, where elements can replicate with the inheritance of features. These algorithms model spacetime by adapting to limited space faster than others at the right time and place (inertia). The replication with inheritance of features involves random variation (Darwinian) or acquisition (Lamarckian) of features, and some elements are more adapted than others and, therefore, have a higher chance of replicating (Steels & Brooks, 2018).

Modeling physical phenomena

Interest of knowledge

When modeling a neural network based on the human brain and memory, a physical process is a sustained phenomenon marked by gradual changes through a series of states occurring in the physical world. Physicists and environmental scientists attempt to model these processes in a principled way through analytic descriptions of the scientist's prior knowledge of the underlying processes and the large amount of data gathered on these phenomena. Conservation laws and physical principles are generally formalized using differential equations.

Jaques Hadamard (1893) argued that mathematical models of physical phenomena should have properties that the solution exists and the solution is unique. For example, de Bézenac, Pajot, and Gallinari (2019) showed how general background knowledge gained from physics could be used as a guideline for designing efficient deep Learning models to predict sea temperatures by demonstrating a formal link between the solution of a class of differential equations underlying a large family of physical phenomena and the proposed model. Experiments and comparisons with a series of baselines, including a state-of-the-art numerical approach, was provided.

Assumptions of information

Although being challenged by statistical machine learning (ML) with a prior-agnostic approach, the physical paradigm is the primary framework for modeling complex natural phenomena when massive datasets are available. These models rely on multiple physical hypotheses and complex systems thinking. However, despite considerable successes in a variety of application domains, the machine learning field is not yet ready to handle