
HoST - Journal of History of Science and Technology
Vol. 17, no. 2, December 2023, pp. 81-99
10.2478/host-2023-0012

VARIA

The Transformation of a Science by a “Technology”: The Case of Astrophysics and the Introduction of Machine Learning

Anne Marcovich

GEMASS, CNRS-Sorbonne-Paris, France

anne.marcovich@gmail.com

Terry Shinn

GEMASS, CNRS-Sorbonne-Paris, France

terry.shinn.cnrs@gmail.com

Abstract: This article explores the transformations of an area of scientific research provoked by the introduction of big data and the possibilities to treat them by Artificial Intelligence. We study these transformations in contemporary astrophysics as it has developed over the last thirty years. These transformations extend from cognitive work procedures to information processing, systems of collaboration between scientists, epistemology and terrain of questions.

Keywords: Astrophysics; Machine Learning; simulation; big surveys; epistemological shift.

© 2023 Marcovich, Shinn.

This is an open access article licensed under the Creative Commons Attribution-NonCommercial-NoDerivs License (<https://creativecommons.org/licenses/by-nc-nd/4.0/>).

Introduction

This article explores the transformations in an area of science brought about by the penetration of an exogenous technology, in particular how the dynamics of said convergence contribute to impact the practices and construction of knowledge. We will study this encounter in the case of astrophysics and Artificial Intelligence (AI) considered here as a technology. Astrophysics has been the site of considerable change since the 1970s. Important questions such as those linked to the expansion of the universe have propelled the launch of big surveys which have in turn produced an increasing volume of astronomical data. The latter constantly required new tools to be treated. As a science, AI has remarkably evolved and developed and has intensively continued to do so since the 1980s;¹ but in this article, we will exclusively examine it with reference to its function and status as a technology used in multiple and diverse domains where big data treatment is required. Of utmost importance, the use of this “technology” is not affected by its transfer into the domains where it is used, which makes it a “research technology” as defined in Terry Shinn and Bernward Joerges.² The development of Machine Learning (ML) in the 1980s (a renewed conception of AI) and the invention of new artificial neural networks,³ made it epistemologically compatible with standing scientific research procedures. In this perspective, ML algorithms constitute a key for treatment of the aforementioned vast amounts of complex information in astrophysics. Simply stated it is here considered a tool.⁴

As signalled above, AI develops and evolves independently along with its proper problematics and kingdoms of research, and it is applied in many diverse sciences, technologies or even social domains without being impacted by these applications. It is its transverse character that makes AI/ML a technology whose multiple applications generate impacts that are worthy of exploration.⁵

¹ This is particularly visible for example in the case of Alphago (<https://www.deepmind.com/research/highlighted-research/alphago>), so continuing the research tradition in AI on Games. For example, Nathan Ensmenger, “Is Chess the Drosophila of Artificial Intelligence? A Social History of an Algorithm,” *Social Studies of Science* 42, no. 1 (2012): 5-30.

² Terry Shinn and Bernward Joerges, “The Transverse Science and Technology Culture: Dynamics and Roles of Research-Technology,” *Social Science Information* 41, no. 2 (2002): 207-51.

³ In the world of AI, the expression “neural network” refers to a network of units in which information is processed and then used for predictive modelling, adaptive control and applications where they can be trained via a dataset.

⁴ This stands in contrast with a scenario where ML is explored as a “science,” or in which ethics problematics are central.

⁵ For example, Shinn and Joerges, “The Transverse Science”; Klaus Hentschel, “Periodization of Research Technologies and the Emergence of Genericity,” *Studies in the History and Philosophy of Modern Physics* 52, Part B (2015): 223–33; Erik Lettkemann, “Nomads and Settlers in the Research Technology Regime. The Case of Transmission Electron Microscopy,” *Social Science Information* 56, no. 3 (2017): 393-415; Terry Shinn and Anne Marcovich, “Science Research Regimes as Architectures of Knowledge in Context: A ‘Longue Durée’ Comparative Historical Sociology of Structures and Dynamics in Science,” *Social Science Information* 59, no. 2 (2020): 310-28.

The empirical basis of our study that explores the powerful interaction between astrophysics and ML largely revolves around numerous, lengthy personal interviews with key researchers dealing with a variety of topics typically constitutive of inputs entailed in astrophysics.

Section one of this article examines the developments within ML which in the 1980s made it attractive for scientific research. Section two explores some methodological cognitive work of the pioneers who first recognized the possibilities offered by ML to address astrophysical questions, such as galaxy morphology or gravitational waves lensing. In the third section of this paper, we will see that since its introduction into astrophysics in the 1990s, ML has come to constitute an important source of change in the form and content of cognitive collaborations within research groups and beyond. Finally, in section four, we treat the sometimes-revolutionary contributions of ML to astrophysics, especially since 2015, when Deep Learning began to be used in this field.

The Birth of Machine Learning in the 1980s

In 1956, the historical Dartmouth Conference, that gathered a large number of scientists from different disciplines, set the stage for the birth of computer-based learning with the ambition to produce machines capable of imitating human intelligence.⁶ Over the next thirty years, innumerable attempts to fulfil this hope followed, but often disappointingly. Up to the 1980s, these ambitions were not of the sort to impact academic scientific research. However, a novel chapter in the history of AI took place during the period beginning in 1984-1986, when a new technological orientation arose making it attractive to disciplinary academic research.

How did this change come to pass? Understanding this change is central to the purpose of this article, as it offers one of the keys to the promotion of communication and partnership between the “new” AI and academic disciplinary research. One must be attentive to the difference between AI and ML. On the one hand, AI which in fact has emerged only very recently with Deep Learning, refers to methods by which a computer makes decisions or discoveries that would usually require human intelligence. On the other hand, ML entails automated processes

⁶ This conference brought together the American cognitive scientist Marvin Minsky (1927–2016) (MIT), the mathematician and computer scientist Seymour Papert (1926–2016) (MIT), the physicist and computer scientist Allen Newel (1927–1992) (Princeton University and Carnegie Mellon University), the mathematician John MacCarthy (1927–2011) (Princeton University), and the engineer Arthur Samuel (1901–1999) (IBM). The participants in this conference exuded hope and the ambition to produce machines capable of “thinking”: Pamela McCorduck, *Machines Who Think; A Personal Inquiry into the History and Prospects of Artificial Intelligence* (San Francisco: W. H. Freeman and Co., 2004).

that learn by repetition of examples in order to classify, predict, discover, or generate new data,⁷ and with it, sometimes decisively new understandings.⁸ We will here principally refer to ML.

Markers of these transformations are associated with the dramatic increase in data processing capacity, and with the development and incorporation of new machine-learning technologies based on artificial neural networks in computer programs. The 1980s saw a profound renewal of neural networks machine-learning capacities, notably with the revival of backpropagation,⁹ the development and diffusion of multi-layer neural networks, and later the exponential growth of the amassing and processing of “big data.” Big data primarily refers to data sets that are too large or complex to be treated by traditional data procedures. The big data “revolution” has brought transformations in the processing and mining of information that has had important epistemological consequences that will be explored below.¹⁰

⁷ Christopher Fluke and Chris Jacobs, “Surveying the Reach and Maturity of Machine Learning and Artificial Intelligence in Astronomy,” *Data Mining and Knowledge Discovery* 10, no. 2 (2020): e1349.

⁸ Christopher Fluke (Professor at the Centre for Astrophysics and Supercomputing-Swinburne University of Technology, Australia), interview by the authors via videoconference, June 4, 2021.

⁹ Backpropagation was introduced in the context of multilayer networks where the problem was to train the system all along its different layers. The method opens the way to efficiently calculate the gradient of cost for each layer in order to minimize it from the output to the entry of the system. This technique is also sometimes called backward propagation of errors because the error is calculated at the output and distributed back through the network layers. Eventually, the first layers can identify the good configurations to be recognized in an image in order to achieve the task. Terry Sejnowski, *The Deep Learning Revolution* (Cambridge, M.A.: MIT Press, 2018); Yan Le Cun, *Quand la Machine Apprend. La Révolution des Neurones Artificiels et de l'Apprentissage Profond* (Paris: Odile Jacob, 2019). These developments are linked to the names of Geoffrey Hinton (1947-), a cognitive psychologist and computer scientist, John Hopfield (1935-), a physicist, and Donald Rumelhard (1942–2011), a psychologist. In 1986, they published an article on backpropagation, which was one of the events linked to the revitalization of research on AI. Other scientists, such as Terry Sejnowski (1947-), a physicist, Yan Le Cun (1960-), an electrical engineer, to cite only a few, participated in this renewal movement. Among the outstanding novelties, Geoffrey Hinton and Terry Sejnowski invented the Boltzmann machine (1985), one of the first neural networks capable of “learning” representations about the world in a form that a computer system can utilize to solve complex tasks, and able to represent and (given sufficient time) to solve difficult combinatorial problems. From 2000 onward, these AI innovations found a home in most AI-related academic science research.

¹⁰ For example, Tony Hey, Stewart Tansley and Kristin Tolle, eds. *The Fourth Paradigm: Data-intensive Scientific Discovery* (Redmont, WA: Microsoft Research, 2009); Luciano Floridi, “Big Data and their Epistemological Challenge,” *Philosophy and Technology* 25, no. 4 (2012): 435–7; Robert Kitchin, “Big Data and Human Geography: Opportunities, Challenges and Risks,” *Dialogues in Human Geography* 3, no. 3 (2013): 262–7; Robert Kitchin, “Big Data, New Epistemologies and Paradigm Shifts,” *Big Data & Society* 1, no. 1 (2014): 1–12 ; Daniel Carter, “Reimagining the Big Data Assemblage,” *Big Data & Society* 5, no. 2 (2018) <https://doi.org/10.1177/2053951718818194>; Dominique Cardon, Jean-Philippe Cointet and Antoine Mazieres, “La Revanche des Neurones. L'Invention des Machines Inductives et la Controverse de l'Intelligence Artificielle,” *Réseaux* 211, no. 5 (2018): 173220. A first characteristic of the new ML that is particularly important in science is what is called the 3V, for Volume, Variety and Velocity. See Yanxia Zhang and Yongheng Zhao, “Astronomy in the Big Data Era,” *Data Science Journal* 14, no. 11 (2015): 1–9.

The capacities and perspectives linked to these and other new ML technologies resonate profoundly and strategically with three historical concerns in academic science: classification, pattern and prediction.¹¹ The question of how their expression inside ML has gradually come to illuminate practices in academic science research is of foremost importance. In ML programs, the aim of classification is discovery of regularities in the inputs. Here, one must introduce a distinction between supervised and unsupervised learning. In the supervised process of learning by the machine, all the categories of information that have to be processed are defined from the outset. The work of the machine is “only” to put each object or phenomenon in the right class. In unsupervised learning, the machine is instructed to engage a process of detection and classification, but with no pre-defined categories. It opens possibilities of discovering previously unidentified-unknown objects/phenomena which is not the case with supervised ML. This entails a subsequent classification of the new item inside extant categories. In certain instances, this sometimes even allows the transformation of said categories. In both cases (supervised and unsupervised), the question to the machine cannot be asked and the results cannot be interpreted by a non-specialist in the area. In our case, an astrophysicist, and even an astrophysicist specialized in the question at stake.

In both situations, data are progressively ordered and classified according to their fit with a scheme which emerges from the integration and organization of more and more data, as progressively deciphered through the machine processes. Concerning unsupervised ML, the pattern which first appears as approximate knowledge of the object or phenomenon under study constitutes the architecture bearing new information that allows the machine to add sophistication to the pattern, and thus little by little to detect new events, objects or phenomena. The machine algorithms integrate more and more abundant data as it allows update to already formed representations of the object under study, and in this same line make predictions.¹² This possibility was magnified by the performance allowed by the introduction of Deep Learning in 2012 (see section 4).

These three categories—classification, pattern, prediction—of ML action lie at the heart of the encounter between ML and the academic sciences (biology, chemistry, physics, etc.) in which it is used.¹³ It makes AI epistemologically compatible with science procedures, and it

¹¹ Soraya De Chadarevian and Nick Hopwood, eds., *Models. The Third Dimension of Science* (Palo Alto, CA: Stanford University Press, 2004); Margaret Morgan and Mary Morrison, eds., *Models as Mediators. A Perspective on Natural and Social Science* (Cambridge: Cambridge University Press, 2004); Hans Jorg Rheinberger, “Infra-experimentality: From Traces to Data, from Data to Patterning Facts,” *History of Science* 49, no. 3 (2011): 337–48.

¹² For example, Ethem Alpaydin, *Machine Learning. The New AI* (Cambridge, M.A.: MIT Press, 2016).

¹³ For example, in biology, we can cite the Alphafold program created by Google in 2022, which can predict the shape of a protein simply by knowing its amino acid sequence, and thus the form and function of this protein. In ecology, the adoption of ML programs is improving the ability to classify underwater images, such as photographs of corals, at species level. Even the anticipation of a higher

is at this very juncture that the transverse quality of ML allows its adaptation to the different problematics pursued in science, and notably in astrophysics. In effect, we will see that the issues of pattern and classification are at the very root of many astronomical questions (for example the classification of galaxies according to their shape, the question of the merger of galaxies, or the detection of gravitational waves); in the very same way as the concept of prediction concerns solar flares as well as exoplanets detection, for example.

Here, the training of the machine requires ever more data in order to enhance precision and reach of results. This has been rendered possible thanks to the invention of the Graphic Processing Unit (GPU) which allowed computers to be increasingly efficient in the processing of images. Invented in the 1970s and repeatedly improved since then, GPUs are a specialized electronic circuit designed in structures that make them highly efficient for algorithms that process large blocks of data in parallel.¹⁴ With GPU systems, big amounts of data can indeed be exploited with an ever-higher speed and precision of treatment.¹⁵ We will see in section 4 that the capacity to accelerate the data treatment procedures has important epistemological consequences, making the information contained in results more precise. With the GPU revolution and the new ML performances, the advent of ever greater amounts of data which the astronomical surveys increasingly provided, the 1990s hastened the introduction and growing penetration of ML into astrophysics.

One can say that the introduction of ML into astrophysics and its capacity to explore huge amounts of information constitutes a sort of weapon by which the scientific field frontiers of astrophysics (but this could be broadened to other scientific fields) could be bridged and could open the door to novel ways of constructing knowledge. It is precisely this transversality which will allow us to identify one of the ways by which ML could penetrate astrophysics. This will be seen in sections 2 and 3.

The Beginnings of Machine Learning in Astrophysics

As discussed above, since the 1970s-80s the demand for observational data to confirm astronomical theories such as the dynamics of galaxies evolution led to the organization and funding of big astronomical surveys. These missions which detect and capture images, for

taxonomic level will be an excellent starting point for further research on a totally unknown specimen. The technique could become a useful tool for predicting and understanding patterns of ecological response to environmental change.

¹⁴ Wikipedia, s.v. “Graphics Processing Unit,” last modified October 6, 2023, 08:35, https://en.wikipedia.org/wiki/Graphics_processing_unit.

¹⁵ Robert Barsdell, David Barnes and Christopher Fluke, “Analysing Astronomy Algorithms for Graphics Processing Units and Beyond,” *MNRAS Monthly Notices of the Royal Astronomical Society* 408, no. 3 (2010): 1936-44.

example of galaxies, in a definite region of the sky, provide a quantity of images which are less and less possible to classify exclusively based on human vision and expertise. This task was initially carried out by individual astronomers, later organized in big citizen science programs (the Galaxy Zoo was launched in 2000) where volunteers from across the world were invited to classify sets of images in relatively simple classes, according to the shape of the galaxies—meeting here the required criteria— classification/pattern. This procedure is still used, but it was quickly felt that human capacities to cope with this avalanche of data were largely exceeded; for the millions of images to be scrutinized and classified, the challenge was increasingly impossible to reach. It was at this juncture that ML was considered a worthwhile instrument to attempt to perform this class of tasks.

Indeed, one of the earliest practices in astrophysics in the 1990s, which used Artificial Neural Networks set out to classify data of galaxy images¹⁶ according to their shape—a long standing problem since Edwin Hubble’s 1930’s work on galaxies.¹⁷ In effect, the issue of galaxy morphology becomes central here as a way to understand internal processes of a galaxy such as the potential formation of stars, or the presence of black holes, among other questions. It is essential to point out here that the major function and power of ML lies in the capacity to identify a category of objects and then to classify them according to pre-decided criteria.

The first article on galaxy classification did not raise new questions in astrophysics,¹⁸ but was instead clearly oriented towards the exposure of a method (the use of Artificial Neural Network),¹⁹ which would subsequently allow an ever more precise classification of galaxy shapes. In view of the huge number of images requiring examination, the human capacity for treatment and analysis for purposes of classification was redoubtable. To introduce the new ML automatic processing technique would be revolutionary. A group of four scientists addressed this acute problem: Ofer Lahav (an Israeli-British astrophysicist),²⁰ Laerte Sodré Junior (a Brazilian astrophysicist),²¹ Michael Storrie-Lombardi (an American physician working on artificial neural networks),²² and his wife, Lisa Storrie-Lombardi (an American astrophysicist).

¹⁶ Solar flares prediction was one of the first subjects to be treated with Neural Networks. Henrik Lundstedt, “Neural Network Predictions of Solar-Terrestrial Effects,” *Planetary and Space Science* 40, no. 4 (1992): 457-64.

¹⁷ Edwin Hubble (1889-1953) had set a system of galaxy classification which mainly focused on the galaxy spiral and the elliptical shape which in his conception, signalled about the age and dynamics of galaxies.

¹⁸ Ofer Lahav, Michael Storrie-Lombardi and Laerte Sodré, “Morphological Classification of Galaxies by Artificial Neural Networks,” *Monthly Notices of the Royal Astronomical Society* 259, no. 1 (1992): 8-12.

¹⁹ Most of its references cite authors who invented neural networks and backpropagation, and not astrophysics works.

²⁰ Ofer Lahav, interview by the authors via videoconference, March 17, 2021.

²¹ Laerte J. Sodré, interview by the authors via videoconference, March 16, 2021.

²² Michael Storrie Lombardi, interview by the authors via videoconference, May 4, 2021.

In the early 1990s, Ofer Lahav, who already held a permanent position at UCL (UK), and the three other scientists holding a post-doc position at the same university, regularly met to discuss their work. The crystallisation of their collaboration took place when they realised that the astrophysics problem to classify their galaxies images could be addressed through the physician’s competence in neural network. On his side, the physician Michael Storrie-Lombardi needed to train his artificial neural network with a sufficient amount of data that his biomedical research on cancer could not yet provide. In effect, ML is thirsty for data in order to be trained for a specific task. At this period, cancer images were not so abundant, contrary to astrophysical images.²³ It is remarkable to notice here that ML functions as a tool that, whatever the context and the type of objects, can differentiate features according to the characteristics chosen to classify them and produce classes with reference to decided criteria. Here the idea was to make it work, be it on galaxy images or on cancer images: what counted was to make the ML program able to select them according to their shape.

The versatile capability of ML technology in this episode highlights an important characteristic: an algorithm developed for a specific area of science can sometimes find fruitful applications in an alternative domain of science. This illustrates the generic trait of the instrument ML as it can identify and classify objects belonging to very distant fields according to a common feature, here the form of the object. ML thus exhibits its “research technology” character via its far-reaching capacity to deal with strongly converging aspects of otherwise often superficially similar but in fact highly different categories of objects. Indeed, algorithms for pattern recognition are largely independent of the objects to which these patterns belong. Astrophysicists use ML technology without recourse to collaboration with ML specialists, although they can solicit advice from the latter. Here, the ML algorithm acts as a transverse tool which can stimulate ongoing collaborations between astrophysics teams working in different domains—²⁴ we will provide inputs of this below in section 3, notably in the case of big surveys. Here we observe the possible formation of bridges even between scientists from different fields. This transverse quality of ML across scientific disciplines is particularly perceptible with the treatment of images. One instance of this is seen in the collaborations between the Cosmostat team and the Neurospin one.²⁵

²³ In fact, they were not using images proper, but instead employed data produced by machine scans of astronomical photographic plates and, through a software predecessor of Source Extractor (invented in 1993 by Emmanuel Bertin) transformed in a series of measurements. The direct use of images only became possible with Deep Learning and GPUs, more than ten years later. Emmanuel Bertin, Institut d’Astrophysique de Paris, interview by the authors via videoconference, November 20, 2020. Emmanuel Bertin and Stephane Arnouts “SExtractor: Software for Source Extraction,” *Astronomy & Astrophysics Supplement Series* 117, no. 2 (1996): 393–404.

²⁴ See note 5.

²⁵ Jean-Luc Starck director of Cosmostat (working in astrophysics) and Philippe Ciuciu, director of Neurospin (working in neuroscience) are both based at the French Commissariat à l’Energie Atomique’s laboratories. They regularly work together and are involved in common projects such as the COSMIC

Through a statistical analysis of huge volumes of data, ML indeed detects patterns undetectable to human eyes. Similarly, the congruence between physical problematics coming from diverse expressions of phenomena other than astronomical reducible to a same principle, constitutes a terrain where, with few adaptations, a same ML algorithm can be applied. For example, shared principles in fluid mechanics govern the dynamics of evolution of galaxies as well as the turbulences in water falls or ocean currents, etc.²⁶ It is essential to note that, while using a transverse technology like ML, only specialists of a specific domain in science are capable of asking questions for said domain and interpret ML results.

It is important to note that until about 2010, performance analysis of the use and power of ML animated an impressive quantity of research in astrophysics. This research was principally methodological-comparison of ML performance with more classical procedures, and between different kinds of ML/neural networks. At this juncture, ML use did not call for a detailed training in computer science. The introduction of ML in astrophysics did not radically transform astrophysics questions, procedures and work. However, it is also important to point out that, during this period, almost all astrophysics topics have at least attempted to integrate ML technologies. But, as will be seen in section 4, it is indeed only with the Deep Learning revolution which occurred in astrophysics in 2015, that astrophysics was deeply impacted by ML.

Toward New Horizons of Collaborations?

As many other scientific fields, over decades, astrophysics became increasingly international, with reference to financing, aspirations, projects, institutions and collaborations.²⁷ The introduction of AI in these collaborations found its way into the framework of scientific activities already strongly reshaped by a preference and context of internationalization. However, the

project funded in 2016 and regularly renewed; they published several articles together, for instance: Zaccharie Ramzi et al., “Wavelets in the Deep Learning Era,” *Journal of Mathematical Imaging and Vision* 65, no. 1 (2023): 240-51.

²⁶ Karim Benabed (Institut d’Astrophysique de Paris), interview with the authors, October 2, 2020. For example, Tianyi Li et al., “Study of Nonlinear Interaction between Waves and Ocean Currents Using High-Fidelity Simulation and Machine Learning,” 33rd Symposium on Naval Hydrodynamics, Osaka, Japan, October 18-23, 2020.

²⁷ Yves Gingras, “Les Formes spécifiques de l’Internationalité du Champ Scientifique,” *Actes de la Recherche en Sciences Sociales*, 141, no. 2 (2002): 31-45; Loet Leydesdorff and Caroline Wagner, “International Collaboration in Science and the Formation of a Core Group,” *Journal of Informetrics* 2, no. 4 (2008): 317-25; Loet Leydesdorff et al. “International Collaboration in Science: The Global Map and the Network,” (2013), arXiv preprint arXiv:1301.0801; Sujin Choi et al., “The Triple Helix and International Collaboration in Science,” *Journal of the Association for Information Science and Technology* 66, no. 1 (2015): 201-12; Leonardo Costa Ribeiro et al. “Growth Patterns of the Network of International Collaboration in Science,” *Scientometrics* 114 (2018): 159-79.

association of competences linked to ML seems to have affected scientific activities cognitively and organizationally which was previously not always the case; in effect, the research processes were found to be disturbed by this transverse technology.

Big research missions, such as the Sloan Digital Sky Survey (SDSS)²⁸ or the Hubble Space Telescope (HST)²⁹ were organized and for the most part launched before the Deep Learning revolution in 2015, when ML was not yet sufficiently effective in astrophysics. In these circumstances, ML was not included in the programs, and it is only now that ML groups are becoming a part of the very tissue of these missions, for example in the case of Euclid,³⁰ where a differentiated team composed of astronomers and computer scientists emerges; the specificity of this team is polycentricity across the different projects in Euclid missions. The astrophysicists, members of such an ML team are, at the same time, permanent researchers in their home laboratory. In this case, algorithms invented in computer science or adapted from alternative astrophysical programs are used for collecting data in astronomical missions – in effect a kind of rake. Indeed, in instances where ML constitutes one of the hubs of a project, its introduction implies reinforcement of interdisciplinary collaborations. For the treatment of the data collected in this instance, dedicated research groups, which are sometimes international, and in most of the cases can mobilize many institutions, are established for the analysis of these data in order to address their defined topics. Here again, ML technological skills are ever more unavoidable and involve an extended variety of competences. Another organization of research work involves informal collaborations between astrophysical teams and enterprises like Google.³¹ This kind of structure-profile, often occurring in the context of big surveys, is organized on a temporary basis which is tending to become increasingly permanent.

Novel configurations of network collaborations are expanding in multiple directions, from the local team of scientists, to informal, far-flung encounters between individuals,³² as well as through structured but more or less temporary collaborations—a very diverse scope of

²⁸ The SDSS, a private/public initiative, is a major multi-spectral imaging and spectroscopic redshift survey. Data collection began in 2000 and continues today.

²⁹ The Hubble Space Telescope is a project of international cooperation between NASA and the European Space Agency (ESA) operating since 2010, and still in activity.

³⁰ Euclid is a space telescope of the ESA, whose launch was scheduled for 2022 and whose observations will contribute to identify the origins of the universe expansion acceleration and the nature of its source generically termed “dark energy.”

³¹ Marc Huertas-Company, interview by the authors via videoconference from Paris, October 28, 2020, translated from French by the authors. Marc Huertas-Company is a researcher at the Institut d’Astrophysique de Paris and is himself a member of temporary teams composed of Google scientists and astronomers.

³² Benoit Semelin (Institut d’Astrophysique de Paris), interview by the authors at the Institut d’Astrophysique de Paris, December 19, 2019, and September 20, 2020.

interests and skills.³³ In this context, new approaches have emerged, such as astroinformatics,³⁴ an interdisciplinary field of study mobilizing the combination of astronomy, data science, ML, informatics, and information/communications technologies.³⁵

Another institution born at the crossroads between astrophysics, big data and ML is the Virtual Observatories (VO), whose initial implementation took place in 2002. Here, the concept is not to gather scientists into a common team, but to collect, centralize and organize existing data from multiple institutions (observatories) and projects/surveys.³⁶ VO are now global. They render available more and more important sets of information which would otherwise remain fragmented or at least uncoordinated. The scientists who nourish them also consume them.³⁷

At a more local level, initiatives have originated transdisciplinary organization of work with the establishment of novel structures of research; the creation of Cosmostat (CEA-France) in 2010 is an example of this.³⁸ Its founder, Jean-Luc Starck, had in mind a well-defined project. To construct a “modern” laboratory of cosmology, he thought that it was imperative to master statistical tools, as astrophysics’ objective is the search for smaller and smaller objects lying within increasingly huge databases.³⁹ For this, it was necessary to mobilize an extensive range of competences (theoretical physicists, observational cosmologists, image signal processing scientists, electrical engineers). All these scientists work together on the same problems. There is no inclination to see specialty knowledge or services lying outside of the lab in order to develop an algorithm. As previously mentioned, to address specific problems in astrophysics it is essential to master the smallest details of the domain. This laboratory is characterized by a mixed culture where each practitioner is competent in statistics/ML as well as in astrophysics.

A key element in the new era of big data and ML lies in the contrast between the huge structures which generate these big data (big surveys), or which assemble them (VO), and their availability to all those interested, and the increasing and measurably open space where

³³ Wesley Shrum et al., *Structures of Scientific Collaboration* (Cambridge, M.A.: MIT Press, 2007).

³⁴ Kirk Borne, “Astroinformatics: A 21st Century Approach to Astronomy,” *Astro2010: The Astronomy and Astrophysics Decadal Survey* (2010): P6. arXiv:0909.3892. Bibcode:2009astro10P...6B. This field was inspired by works in the areas of Bioinformatics (first coined in 1970, but really developing in the 1990s) and Geoinformatics (appearing in the early 1990s).

³⁵ Astroinformatics is indeed sometimes regarded as the “Fourth Paradigm” of astronomical research. Hey, Tansley and Tolle, *The Fourth Paradigm*. Wikipedia, s.v. “Astroinformatics,” last modified September 5, 2023, 23:25, <https://en.wikipedia.org/wiki/Astroinformatics>.

³⁶ George Djorgovski and Robert Williams, “Virtual Observatory: From Concept to Implementation,” *From Clark Lake to the Long Wavelength Array: Bill Erickson’s Radio Science, ASP Conference series 345* (2005), 517.

³⁷ George Djorgovski (Center for Data-Driven Discovery-California Institute of Technology), interview by the authors via videoconference, March 16, 2021.

³⁸ <http://jstarck.free.fr/CosmoStat.html>

³⁹ Jean-Luc Starck at Cosmostat (Saclay), interview by the authors, September 22, 2020.

individual practitioners enjoy the freedom of autonomy and, at the same time, the possibility to operate jointly. After about three months, the data become universally accessible. In this evolution of astrophysics, one observes the development of highly elastic research ensembles – extending from highly temporary collaborations to permanent teams engaged in big surveys, including occasional small groups located in distant laboratories. One can say that ML opens the way to novel horizons of collaboration between individual scientists and between established groups, thus embracing unheard possibilities.⁴⁰ Scientists can elaborate their investigation both at a highly individual level with their personal laptop, and in intensely populated big structures. This represents the transformation of the sociology of work in this research domain, thus exhibiting the power of convergence in terms of association and integration. Can a more diverse organization of work be imagined?

The Revolution of Deep Learning 2012-2015

Whereas previously ML was used for specific questions such as galaxy classification, star galaxy separation or solar flares prediction, little by little ML has now become truly ubiquitous among the plural research fields of astrophysics: exoplanet identification, massive black hole detection, star formation in galaxies, etc. Since around 2010, all the topics constitutive of astrophysics have indeed been touched by ML. However, while ML results in astrophysics showing good percentages of success, they were nevertheless not staggering until the introduction of Deep Learning.

In the world of computer scientists, investigations in the domain of AI and ML have accelerated at an extraordinary pace since 1990. This research has developed profitably thanks to the financing bulldozer of companies such as Google or Facebook, which exceed the involvement of universities. It was indeed in this context that Deep Learning was invented in 2012.⁴¹ Even though the principles and initial applications of multi-layer networks date from the 1980s, it was not until the 2010s that the Deep Learning revolution occurred, due to the above-mentioned GPU and to the accelerated development of big data sets.

Deep Learning has inaugurated a new step forward in the marriage between computer science and plural scientific fields. It indeed allows computational models composed of multiple layers to learn representations of data. It nests structure in large data sets by using the backpropagation algorithm to indicate how a machine should change its internal parameters that are used to

⁴⁰ See note 5. Terry Shinn and Anne Marcovich, “Where is Disciplinarity Going? Meeting on the Borderland,” *Social Science Information* 50, no. 3-4 (2011): 1–25; Judy Olson and Gary Olson, *Working Together Apart: Collaboration Over the Internet* (n.p.: Springer Nature, 2022). It would however be an exaggeration to think that ML is the sole factor in this evolution.

⁴¹ Sejnowski, *Deep Learning*; Le Cun, *Quand la Machine Apprend*; François Chollet, *L'Apprentissage Profond avec Python* (n.p.: Machine Learning.fr Editions, 2020).

compute the representation in each layer from the representation in the previous layer.⁴² It is able to treat increasingly complex and abundant data, and thus to construct a solution for a given problem. Deep Learning, which was first developed to solve problems of fraud, or to drive autonomous cars, promotes important progress in science in this instance—in particular finding a solution for non-linear problems (such as the evolution of a system where the big number of parameters triggers discontinuities within the process of evolution),⁴³ a huge advance in science applications. Most of the scientific disciplines were drawn to the use of Deep Learning almost from its inception, as it was viewed as particularly relevant to solve long lasting problems in different areas of science. For example, as already indicated in note 13, in biology the issue of predicting the protein structures could be effectively addressed, and in 2021 the first program which could determine a protein structure from its amino acids sequence was launched by the Google team “DeepMind” and became available, with the AlphaFold program.⁴⁴ This testifies to the fact that Deep Learning very rapidly found a market in many scientific disciplines.

The 2005-2010 and beyond period also constituted a moment of transition where bigger and bigger surveys began to be organized,⁴⁵ and which were supposed to produce even more data than the preceding ones – instead of millions of images of galaxies, they are expected to generate billions, a task that the citizen project would take a hundred years to do. Indeed, that was not the task for the preceding adventures. A tsunami of data generated by increasingly complex and big instruments began to nourish data sets and research programs that could only be dealt with by Deep Learning machines. For example, the most ambitious project in astronomy—the Square Kilometre Array,⁴⁶ with its 2000 radio dishes and 2 million low-frequency antennas, is expected to produce more than one exabyte per day.⁴⁷ This is more than the entire internet for a whole year, produced in just one day! This revolution in data generation and treatment quickly stimulated efforts in all fields of investigation. The amassing of historically unprecedented data

⁴² Yan Le Cun, Yoshua Bengio, and Geoffrey Hinton, “Deep Learning,” *Nature* 521 (2015): 436-44.

⁴³ Notably Karim Benabed (Institut d’Astrophysique de Paris), interview by the authors October 2, 2020, and Emeric Bron (Observatoire de Paris), interview by the authors via videoconference, November 12, 2021; Frédéric Courbin (Ecole Polytechnique Fédérale de Lausanne), interview by the authors via videoconference, May 15, 2021.

⁴⁴ The article announcing this discovery was published in *Nature* in August 2021 and has already been cited 4906 times: John Jumper et al., “Highly Accurate Protein Structure Prediction with AlphaFold,” *Nature* 596 (2021): 583-89 (already cited more than 10,000 times).

⁴⁵ For example, Euclid (see note 30) or the Large Synoptic Survey Telescope LSST. The LSST is scheduled to operate for 10 years (beginning in 2022) and will sweep the entire sky several times weekly in order to generate a 3D panorama of the universe.

⁴⁶ SKA, an intergovernmental radio telescope being built in Australia and South Africa with projected completion around 2030. Wikipedia, s.v. “Square Kilometre Array,” last modified September 14, 2023, 04:34, https://en.wikipedia.org/wiki/Square_Kilometre_Array.

⁴⁷ Henry Joy McCracken (Institut d’Astrophysique de Paris), interview by the authors via videoconference, October 26, 2021.

made sense only if that data could be processed and mobilized for cognitive purposes. This made sense only if a new relationship between astrophysical fields and the technology of Deep Learning emerged.

As stated above, between 2005 and 2010, citizen sciences programs were launched, particularly in astrophysics with the galaxy zoo.⁴⁸ This would prove particularly useful as it generated training samples for the machines which were to follow, and which would rely on ever richer databases. When the Deep Learning revolution occurred in astrophysics in 2015, everything was in place as all these samples were already classified by the citizens which had taken years to perform. The first articles in astrophysics whose ambition was to classify galaxy morphologies with Deep Learning notably surpassed all that had been published before in the field.⁴⁹

The accumulation of billions of data through different surveys, and the diverse research topics and their encounter and mixing, resulted in the complexification of combinations of inputs and results where, along with renewed statistical methods, ML procedures could play an important role. Linked to these efforts, simulation became ever more important.⁵⁰

This growth is illustrated by the number of publications per year: in 1984 the number of publications with simulation in astrophysics stood at one, in 2000, 134 publications, in 2010, 300 publications and in 2020, an astonishing 645 publications.⁵¹ The laborious work of simulation which indeed can take months to obtain an answer, requires already processed data, a task which is increasingly undertaken by ML. Conversely, since the work of Emmanuel Bertin in 1996,⁵² when an ML algorithm first used simulation data to be trained, this procedure has been increasingly used. Here one observes a synergy developing between simulation and ML. In a word, Deep Learning not only can treat billions of data, but also is associated in

⁴⁸ Wikipedia, s.v. “Galaxy Zoo,” last modified September 20 2023, 18:03, https://en.wikipedia.org/wiki/Galaxy_Zoo.

⁴⁹ Sander Dieleman, Kyle Willett, and Joni Dambre, “Rotation-invariant Convolutional Neural Networks for Galaxy Morphology Prediction,” *Monthly Notices of the Royal Astronomical Society*, 450 (2015): 1441–59; Marc Huertas-Company et al. “A Catalog of Visual-like Morphologies in the 5 CANDELS Fields using deep-learning,” *The Astrophysical Journal Supplement Series* 221 (2015): 8; Marc Huertas-Company et al., “Deep Learning Identifies High-z galaxies in a Central Blue Nugget Phase in a Characteristic Mass Range,” *The Astrophysical Journal*, 858 (2018): 114.

⁵⁰ Roman Teyssier, “L’Univers dans un Ordinateur: La Simulation Numérique à la Conquête des Astres,” conference at the IAP, Paris, 12 December 2006, accessed February 8, 2023. https://www.canal-u.tv/video/cerimes/l_univers_dans_un_ordinateur_la_simulation_numerique_a_la_conquete_des_astres.9256. Guihem Lavaux (Institut d’Astrophysique de Paris), interview by the authors, October 6, 2020. Frédéric Courbin (Laboratoire d’Astrophysique de l’Ecole Polytechnique Fédérale de Lausanne), interview by the authors via videoconference, May 7, 2021.

⁵¹ Isiweb research under the topics: “simulation” and “astrono*.”

⁵² See note 23.

an increasingly efficient way to simulation, thus accelerating computation processes in these simulations.

Through this association, from being a strictly observational science, indeed astrophysics has taken the path to becoming also an “experimental” science: in changing certain elements of the equation of the initial conditions of a system, one discovers other scenarios connected with particular descriptions and explanations of the events or processes in the sky.⁵³ Here one discerns ways in which ML contributes to the transformation of key chapters of astrophysics. In the words of the astrophysicist Marc Huertas-Company, who is one of the first to have used Deep Learning throughout astrophysics and whose work has classified galaxies according to their shape:⁵⁴

In astrophysics, the evolution of a celestial object is impossible to capture due to the time scale of millions of years. Therefore, when we observe a galaxy, we observe the picture of this galaxy, but will never be able to see how it evolves. . . . Using very powerful computers, we are able to establish the universe initial conditions, then to introduce the physics that we know, and then we know how to make the system evolve in an accelerated movement, . . . we see whether it fits with our observations. . . . Here, one can use Deep Learning, precisely in order for it to learn the evolution of a specific object depicted in the simulation film and subsequently, that it goes in the static observations and says: ‘that particular object is at this stage of its evolution,’ and thus capable of reconstructing its history. This is entirely new that the machine, through intense training on many simulation films, is able to identify a history of evolution in the astronomical objects.⁵⁵

Beyond the case of retracing the history of a portion of the sky, the association of Deep Learning and simulation opens horizons which go beyond the categories of classification, pattern and prediction. It opens the way for the treatment of the highest degree of complexity in the understanding and prediction of non-linear processes and in their consequences, thus making it possible to set an experimental procedure on dynamical processes in the universe. The association of Deep Learning with simulation allows the development of novel lines of reflexion and research in thus far unexplored directions.

The evolution of knowledge on gravitational lensing provides another example of possibilities of asking questions associated with the acceleration of data processing.⁵⁶ The declarations of Yashar Hezaveh (astrophysicist and cosmologist at the University of Montreal) illustrate this:

⁵³ For example, Francisco Villaescusa-Navarro et al. “The CAMELS Project: Cosmology and Astrophysics with Machine-learning Simulations,” *Astrophysical Journal* 915, no. 1 (2021) arXiv:2010.00619.

⁵⁴ Marc Huertas-Company et al., “A Catalog,” 8.

⁵⁵ Marc Huertas-Company, interview by the authors via videoconference, Paris, October 28, 2020, translated from French by the authors.

⁵⁶ A gravitational lens is a distribution of matter (such as a cluster of galaxies) between a distant light source and an observer that is capable of bending the light from the source as the light travels towards

In the 2010s, we only knew a handful of gravitational lenses. . . . So right now, the number of gravitational lenses that we know are maybe a thousand, but the analysis of these have been very slow and hard....Now, think about it ! – in three, four years with big surveys like LSST,⁵⁷ with ML, we’re going to have two hundred thousand lenses. And two hundred thousand lenses, I can model them within half an hour. So all of a sudden I can just kind of think about problems from a very different perspective, so instead of spending a year on cherry-picking one lens, within an hour, I can just model all the lenses, two hundred thousand of them....I think it’s really going to allow to take the strong lensing science to a completely different level of questions that could be answered...And for example, because these lenses are at different redshifts, they’re at different stages of the history of the universe, then I can ask questions, for example: ‘Is there an evolution in the history of the universe in terms of dark matter?’”⁵⁸

The issue of acceleration induces the explosive development of combination of questions such as gravitational lenses with galaxies and star detection, the dark energy origins with the expansion of black holes.⁵⁹ Questions and studies converge thanks to Deep Learning and to the acceleration that it allows in treating data and in associating problems that were previously separated. The combinatorials in topics can increase in an exponential movement, so making the scientific field ever more complex. The power of treatment by Deep Learning for the data issuing from observation and simulation largely open the frontiers of this field. The transversality which characterizes Deep Learning makes it a powerful tool of transformation of the fields where it is used.

The accumulation of highly detailed observational data, where ML also figures centrally (in the above example the rate of gravitational lensing discovery grows exponentially), the capacity in processing and analysis of huge amounts of data, and the acceleration for performing the aforementioned operations, open new vistas of scientific queries. The landscape of research activity becomes increasingly exacting and broad, thanks to an ever-closer relationship with ML technology – an epistemological shift which invites additional studies.

The increasingly growing performance of Deep Learning in astrophysics raises another question: the issue of training novice astrophysicists for entry into today’s research market. A double training (in astrophysics and in ML) is increasingly required for young scientists recently recruited for astrophysical research teams.⁶⁰ Initiatives for training researchers in this

the observer.

⁵⁷ See note 45.

⁵⁸ Yashar Hezaveh, interview by the authors via videoconference, June 2, 2021.

⁵⁹ Ofer Lahav et al., eds., *The Dark Energy Survey. The Story of a Cosmological Experiment* (n.p.: World Scientific, Default Book Series, 2020).

⁶⁰ Anne Marcovich and Terry Shinn, “When Two Science Disciplines Meet: Evaluating Dynamics of Conjunction. The Encounter Between Astrophysics and Artificial Intelligence,” *Social Science Information* 60, no. 3, (2021): 372–77.

new “double” field are being established. For example, a centre for doctoral training in data science and astrophysics is being developed at UCL, under the direction of scientists namely Ofer Lahav,⁶¹ one of the pioneers in ML (see above).

It is to be noted that in this context, astronomers work less and less with raw data but rather on the information that the machines will have extracted from data. This raises the question of trust in the results provided by the machine and the hidden processes inside the black boxes of the deep layers of the neural networks.⁶² In effect, it is impossible for a human mind to follow and understand the series of operations executed by the machine on billions of data with thousands of parameters. Between the hypotheses of work formulated by the scientists, the collection of data by the big instruments, their treatment by the ML programs, the measures that these algorithms provide from the data, and the work on these measurements by scientists (with some other possible steps such as numerical simulation work), and finally the results of a research, one observes a bridge whose parts and connections are not singly intelligible. In these circumstances, one has to be confident in the architecture of the bridge. Scientists continue to cross it and make more similar bridges, but recognise the shadow that envelops the texture of the bridge. This induces a key issue which confronts the scientific procedures lying at the very heart of research: reliability, reproducibility and verifiability of results and their falsifiability which are the criteria of science—a matter of divide between a minority of scientists. Some consider that this is not science, precisely because of these arguments of falsifiability and reproducibility, but also because they consider that though ML permits discovery of new objects or their classification, it is not science in its own right.⁶³ They consider this is just a technology. A greater proportion of scientists consider that ML paves the way for, in the words of George Djorgovski, “a new way of doing science.”⁶⁴ Deep Learning can be understood as the dawning of a new chapter in the history of science whose contours are yet to be explored.

Conclusion

The ancient science, astronomy/cosmology/astrophysics, has experienced constant and sometimes radical metamorphosis since the 1960s: instruments have become increasingly precise and sophisticated, big surveys have been conducted, novel specialties arose, larger and larger quantities of data are being gathered to such an extent that it is not always possible to

⁶¹ Ofer Lahav, interview by the authors via videoconference, March 17, 2021.

⁶² Marcovich and Shinn, “When Two Science Disciplines Meet.”

⁶³ For example, Chris Anderson, “The End of Theory: The Data Deluge Makes the Scientific Method Obsolete,” *Wired*, June 23, 2008; Paul Edwards et al. “Science Friction: Data, Metadata, and Collaboration,” *Social Studies of Science* 41, no. 5 (2011): 667–90.

⁶⁴ Djorgovski and Williams, “Virtual Observatory.”

extract information and formulate rigorous conclusions during the time period preceding the introduction and development of ML in astrophysics, where new collectives are emerging.

AI gave birth to ML in the 1980s, and then to Deep Learning in 2012. Computer science produces tools that are useful for multiple fields: robotics, finance, justice, economics and in different science disciplines among them, geology, climatology, biology, all since the 1990s. This theatre of elements and intervention once again testifies to the transverse character of ML. But an acute knowledge of the field in which ML is to be applied is a prerequisite. Indeed, the ML algorithm to hand has to be precisely adapted in order to address the scientific research question.

As seen above, the increasing performances of AI in astrophysics have resulted in the acceleration in the research processes, but also in the complexification of this scientific field; a complexification which opens new avenues in research projects but also in the transversal character of this very tool as it determines interlacing between different subfields and questions. Beyond this, the training in a specific scientific field constitutes an important issue that has yet to be addressed.

The integration of ML procedures in scientific works points to another important issue: as noticed above, with the introduction of ML in the different science fields, it becomes impossible to follow the steps pursued by the ML programs to produce results.⁶⁵ This induces a key issue which confronts the scientific procedures lying at the very heart of research: reliability, reproducibility and verifiability of results and their falsifiability, which are the criteria of science.

With the integration of ML algorithms in research procedures, astrophysics is taking new paths in the exploration of questions. But this is not only a matter of treatment of big quantities of data, but also of acceleration in processing them. Such acceleration in itself constitutes a factor of transformation in the process of research work and also in new ways of constructing knowledge in astrophysics. Hypotheses and theories can be more speedily tested; the capacity to formulate novel hypotheses and explanations is multiplied. All these elements point to the fact that astrophysics and ML are not only in a simple encounter or association, but instead operate in a veritable dynamical “alloy.” Here the difficult question of alchemical decoding remains, both on an epistemological and on a sociological level. Comparison with study of encounters between ML and other scientific fields may lead to a better understanding of what is at stake here. This is an essay of exploration of history in the very course of transformation. It calls for a larger hindsight.

⁶⁵ Jean-Luc Starck, interview by the authors at Cosmostat (Saclay), January 20, 2020.

Acknowledgements

We wish to express our deepest thanks to the following : Karim Benabed, Emmanuel Bertin, Marc Huertas-Comanie, Guilhem Lavaux, Henry Joy McCracken, Emeric Bron, Tom Charnock, Benoît Semelin (re-searchers at the Institut d’Astrophysique de Paris, Observatoire de Paris, France), Jean-Luc Starck and François Lanusse (Cosmostat, CEA-Saclay, France), Frederic Courbin (Observatoire de Sauverny, Lausanne, Switzerland), Stanislav G. Djorgovski (Center for Data Driven Discovery, CalTech_USA) ,Christopher Fluke (Centre for Astrophysics and Supercomputing, University of Melbourne, Australia); Yashar Hezaveh (University of Montreal, Canada), Ofer Lahav (Department of Physics and Astronomy, University College London, UK), Laerte J. Sodré (Instituto de Astronomia, Geofísica e Ciências Atmosféricas, Universidade de São Paulo, Brazil), Michael Storrie-Lombardi (Astrobiology Kinohi Institute, California, USA), for their openness and patience when answering our questions. This research would not have been possible without their participation.

Competing interests

The authors have declared that no competing interests exist.