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AI for Digital Humanities and Computational Social Sciences

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AI raises multiple essential issues for the humanities and the social sciences. AI is obviously a major societal issue whose consequences are currently invading the public sphere raising a variety of questions of acceptability, privacy protection or economic impact, and involving expertises that span across the entire range of social and human research. But AI is also a new way of doing research, where massive data processing is made possible by techniques of machine and deep learning, offering new perspectives for analysis.
Reflecting about the nature of intelligence and humanity, but also helping the humanities and the social sciences to benefit from the methodological advances of AI: this is the double challenge that this chapter would like to tackle.

I. AI as an object or research

1. AI and the History of Science

The emergence of AI as a scientific and industrial tool is identified with the 21st century, to the point of becoming its emblem. However, if the operational conditions of AI (the availability of large datasets, the computing power and mathematical methods) as well as the first glimpses of what would be a "General AI" (or "Strong AI") are recent, AI it is nevertheless a historical object—and perhaps even an old concept—loaded with our fantasies towards non-humans and with a very long process of formalization, mathematization and datafication of the world. While we often consider AI as our future (if not as an end of time), this future roots in a long history that need to be put into perspective by Human and Social Sciences.

AI took its first steps in the 1950s (with the publication of Alain Turing's seminal article "Computing Machinery and Intelligence"[1] and with the introduction of the label by John McCarthy at a summer workshop at Dartmouth College in 1956), but its archaeology and its accelerated contemporary modulations belong to the historians of Science and Technology Studies. These must take into account a field that strongly involves the history of mathematics (from formal reasoning, whose history is ancient, to contemporary linear algebra), new disciplines (information theory, cybernetics, computer science) and crossovers with exogenous disciplines (economics and its decision theories, cognitive sciences, computational neurobiology, connective approaches, etc.). This helps explain why AI is structured into so many sub-disciplines (speech and image processing through signal analysis, natural language analysis, etc.) and mobilizes so many methods, from symbolic AI to contemporary statistical approaches in response to increasingly ambitious challenges. Mobilizing complex theories of

[1] Alan Turing, "Computing Machinery and Intelligence", *Mind,* 1950, 433-460. 59, 433-460.

knowledge as much as industrial technologies, AI is much more than a "research program"[2] in the sense of Feyerabend and Lakatos: it builds particularly original bridges between biology and mathematics, rethinking the unity of scientific knowledge through a new tree of sciences and imposing a strong epistemological reflection to historians and philosophers.

2. AI and its Imagination

In the mezzanine of the Denon wing, the Louvre museum keeps an impressive automaton, an articulated totem mask representing the jackal-headed god Anubis.[3] This mask and the *Treatise on Automata* by Heron of Alexandria, a Greek mathematician and mechanic, dates from AD 125, reminding us that the contemporary fantasies and fears raised by mechanical intelligence are in fact very ancient. AI is preceded by the ancient legend of the bronze giant Talos, the mechanical guardian of Crete, his prodigies are dreamt of by many medieval myths, from the automatic soldiers protecting the relics of Buddha evoked by the Indian Lokapannatti to the famous Golem, a clay figure that comes to life when a paper with the name of God is placed in his mouth. From the famous steam-powered animated bird created in the 380s by Archytas of Taranto, a friend of Plato's, to the articulated lion imagined by Leonardo da Vinci, from the Chinese androids capable of singing of the Zhou dynasty to the mechanical waitress invented by the Arab engineer Al-Jazari, the tradition of automatons feeds reveries about the magical potential of anthropomorphic machines, but also nightmares about the replacement of humans by superior forms of life, offering a troubling view of the human condition as seen *from the outside*.[4]

Contemporary ethical questions about "moral machines" and economic fears about the robotization of labor cannot be separated from the myths that come with them.[5] Few are the cases in which artificial intelligence has the kindness of the digital geisha played by Scarlett Johansson in Spike Jonze's movie *Her*, who, realizing that her "operating system" has outgrown human intelligence, leaves her human owner to live her own life. From the *Terminator* to Ridley Scott's very recent *Alien the covenant*, the fear of human domination by artificial intelligence, robots or cyborgs or software that has become superior and dreams of exterminating it, looms large. Theorized in 1993 by the science fiction writer Vernor Vinge, the "Singularity" is the name often given to the moment in which robots would take over humanity, leading to the end of history as an asymptote of human progress since the Cartesian project of making oneself "master and possessor of nature."

In this eschatology of the American futurologist Ray Kurzweil (who works Google's natural language processing program), machines would overcome human intelligence in a few decades with the risk of consuming earth's resources for their own benefit. According to his "gray jelly" theory, the combination of AI with developments in nanotechnology and synthetic

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[2] See Martin Farrell, "Lakatos and Feyeraben : research programmes and anarchism", *in Historical and Philosophical Foundations of Psychology*, Cambridge: Cambridge University Press, 2014, 46-68.

[3] Mask (?) of a dog, representing Anubis or Qebehsenouf, with movable jaw, Egypt, 21th dynasty (c. 1069-945), h: 19 cm, w: 11 cm, Paris, Louvre museum, N4096.

[4] See Ada Ackerman (dir.), *Golem ! Avatars d'une légende d'argile*, exhibition catalogue, Paris: MahJ/Hazan, 2017. Laurence Bertrand-Dorléac (dir.), *Artistes & Robots*, exh. cat., Paris: RMN, 2018.

[5] See Jeremy Rifkin*, The End of Work: The Decline of the Global Labor Force and the Dawn of the Post-Market Era*, New York: Putnam Publishing Group, 1995.

biology would allow machines to gain consciousness and lead to an "age of spiritual machines." This is the time of the "Promethean shame," a concept developed by the German philosopher Gunter Anders, which refers to man's feeling of weakness and imperfection in the face of the perfection of the creatures created through his mastery of science.[6]

Think of Philip Dick's famous *Blade Runner*, the magnificent series *Westworld*, which tells the story of the empowerment of androids becoming conscious and free, or *Deus ex machina*, where the main character opens his arm to verify that he is not himself a machine: at a time when deep learning and neural network algorithms are triumphant, submissive or revolted, man sees himself as a robot like any other and discovers in the machine's gaze his disturbing banality. Beyond its political and ethical dimension, the myths of AI thus question the humanity of man and therefore belongs to anthropology as much as to other human and social sciences.

II. AI as a research method

As the foundations, history and imagination of AI are being questioned by the humanities and the social sciences, the new empirical approaches introduced by AI is changing the way Social and Human Sciences model and analyze their data, understand their objects and visualize their results. The emerging applications of machine learning in Social and Human Sciences may eventually concern economy, sociology, geography or archaeology in all the tasks of location and classification. First emerged in the field of image recognition, applications of machine learning have soon extended to other types of data and tasks including printed characters, handwriting and speech recognition, but also financial prediction in the financial, decision support in law or medicine as well as machine translation.

1. Text, Language and Data Analysis

Recent years have seen the production of increasingly large textual corpora for the SHS. Emblematic examples are offered by the digitization of the gigantic Gallica documentary collection by the Bibliothèque Nationale de France, heritage databases and by conversational corpora extracted from social media. Access to massive data offers new perspectives to an increasing number of disciplines, from the socio-political analysis of online conversation to *distant reading*[7] of literary corpus, from cultural to economic history, from linguistics to philology[8].

Going beyond simple statistical studies, the methods of text mining resulting from AI modify key questions of information retrieval, text classification, linguistic and semantic annotation, information extraction, and authorship discovery. *Topic modeling*,[9] automatic classification of documents by machine learning, semantic analysis by word vectors, automatic annotation and

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[6] On Singularity, see Jean-Gabriel Ganascia, *Le mythe de la Singularité. Faut-il craindre l'intelligence artificielle ?,* Paris : Seuil, 2017.

[7] See Franco Moretti, *Distant Reading*, London/New York: Verso, 2013.

[8] See Alexandre Gefen. "The Empirical Turn of Literary Studies" in Nicoletta Pireddu. *Reframing Critical, Literary, and Cultural Theories*, Palgrave Macmillan, Cham, pp.119-135, 2018.

[9] On this technique see http://mimno.infosci.cornell.edu/topics.html.

discovery of named entities, sentiment analysis, have all opened up new perspectives by making possible new quantitative or quali-quantitative text analyses of texts considered as data of contemporary culture or cultural history. This marked the birth of a new discipline called culturomics or cultural analytics, which aims at "extending the frontiers of rigorous quantitative investigation to a wide range of new phenomena covering the social sciences and humanities."[10] The combination of these new algorithms, on the one hand, and the indexing of millions of books and texts, on the other, allows capturing the lexical or grammatical evolution of languages,[11] or to pinpoint literary motives that could have not been noticed by some "human" distant reading.[12]

Through the analysis of texts—itself influenced by the appearance of new algorithms and gigantic corpuses—artificial intelligence has taken its place in the field of economic and social sciences.[13] In particular, "topic modeling" algorithms, developed by the computer scientist David Blei in order to determine abstract topics or themes in texts,[14] were the first to be imported into sociology. These algorithms allow analyzing the actors' discourses and to identify discursive patterns and interpretative frameworks. For example, in collaboration with David Blei, Paul DiMaggio and Manish Nage were able to analyze the American federal government's policy on arts funding through a corpus of 8,000 articles published in major American newspapers between 1986 and 1991, by identifying the moments when certain interpretative frameworks took the upper hand in the public debate.[15] Similarly, in economics, topic modeling can be matched with traditional methods, such as descriptive statistics or econometrics. For instance, the hammer prices of artworks at Parisian auction in the 19th century have been explained through the usual variables of artist attribution, date of creation, dimensions, medium, pedigree, etc., but also through to the "sentiments" of the experts, when they described the artworks in a more or less laudatory way in the auction catalogues.[16]

Far from replacing human researches in economic and social sciences, topic modeling or sentiment analysis have become tools for sociologists and economists, who remain in charge of the interpretation of findings. Moreover, the possibility of interpreting these results is the criterion that ensures the "scientificity" of these disciplines, distinguishing them from approximate methods. In "traditional" econometrics, parametric regressions are computed using an algebraic formula, bound to yield exact, unique, optimal and tractable solutions,

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[10] Jean-Baptiste Michel, Yuan Kui Shen, Aviva Presser Aiden Presser *et al*, "Quantitative Analysis of Culture Using Millions of Digitized Books", *Science,* 2010, 331, 6014, 176: 182.

[11] For instance, Franco Moretti and Dominique Pestre, "Bankspeak. The Language of World Bank Reports", *New Left Review*, 2015, 92, 75-99.

[12] See Yuanfeng Lu, *Caractérisation des genres/styles littéraires par l'extraction automatique des "motifs" dans les romans du 19e et 20e siècle*, ongoing Ph. D. supervised by Thierry Poibeau, PSL / ENS.

[13] See Jean-Philippe Cointet and Sylvain Parasie, "Ce que le *Big Data* fait à l'analyse sociologique des textes. Un panorama critique des recherches contemporaines", *Revue française de sociologie*, 2018/3, vol. 59, 533-557.

[14] David Blei, "Probabilistic Topic Models", Communications of the ACM, 2012, 55, 4, 77-84.

[15] Paul DiMaggio, Manish Nag and David Blei, "Exploiting affinities between topic modeling and the sociological perspective on culture: Application to newspaper coverage of U.S. government arts fundig", *Poetics*, 2013, 41, 5, 570-606.

[16] Thierry Poibeau and Léa Saint-Raymond, "Pricing Opinion and Tastes: The Art Market through Sentiment Analysis", DH2020@Ottawa. This paper uses "Sentiment analysis" algorithms, measuring the "general feeling" of a text, *i.e.* the "positive feeling" or "negative feeling" associated with that text.

which are transparent and available for interpretation. The methodology differs from machine learning models that rely on approximate optimization. Based on variables such as age, place of residence, gender, these algorithms can predict wages or behaviors, but offers little insight about the reasons explaining them.[17] Contrary to the parametric regressions, they constitute a black box and do not offer interpretable coefficients.

With the capability to "*operationalize*,'[18] that is, to transform theoretical or historical hypotheses into operators that can be empirically measured, the propositions of human sciences become more quantitatively verifiable. The masses of data into which cultural history is transcribed allows the critic to test hypotheses formulated by erudition but otherwise difficult to establish because founded upon a general knowledge, a memory of the works, an intuitive synthesis that are difficult to objectivize and to refute. The possibility of aligning human sciences with other sciences[19] raises institutional and scientific questions and impact the visibility and influence of the humanities. In particular, they raise a paradox connected to the fact that these supposedly more verifiable methods so complex and computationally demanding that only to a handful of researchers and institutions can afford to use them. Emerging domains like the quantitative history of ideas or quantitative formalism force us to deal with the opacity of digital black boxes while dealing with massive datasets and complex modeling and interpretation questions that require field intuition and old-style knowledge of corpora.

At the same time, computational linguistics has made dazzling progress, as evidenced by the spread of conversational agents, the contemporary efficiency of machine translation, and the now familiar tools for summarization and grammatical check. Combined with voice or optical recognition, real-time translation has become a reality on smartphones, leading us to dream of a world where linguistic differences will no longer represent cultural barriers. NLP (natural language processing) algorithms trained on large corpora have demonstrated their ability to produce morphological and semantic analyses without the need to parallel translation blocks, encode syntactic or semantic rules, or reducing richness of word semantics. Such advances, embodied by the success of the BERT algorithm used by Google and based on a bidirectional analysis of the context of words, have been made possible by a shift from rule-based analysis (in the 1970s, linguistics postulated, following Noam Chomsky, that natural languages could relate to computer languages) to empirical statistical models that allowed. At the same time, psycholinguistics has been trying to produce neural networks models of the human brain and to emulate how a child learns human language. While many facets of human expression are still resistant (the use of metaphors or irony, for example), some of the tools for automatic text generation are beginning to be used, for example to produce journalistic articles about with sports, company or election results, with the horizon set by artificial intelligence storytelling.

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[17] Julien Boelaert and Étienne Ollion, "The Great Regression. Machine learning, Econometrics, and the Future of Quantitative Social Sciences", *Revue française de sociologie*, 2018/3, vol. 59, 475-506.

[18] See Franco Moretti, « Literature, Measured », Literary Lab Pamphlets, n° 12, avril 2016. Web. https://litlab.stanford.edu/LiteraryLabPamphlet12.pdf.

[19] This is a recurrent ambition that can be observed at every change of scientific paradigm. We can certainly find it in the positivist thought of literary history or in the linguistic turn and the horizon constituted by formal linguistics.

Beyond the temptation of a new positivism, this mathematization of the proof has profound effects. Artificial intelligence supporters claim that theory can be entirely replaced by machine learning algorithms capable of drawing, by induction, general laws or regularities. They dream of an empiricist approach that would render theoretical propositions obsolete and go as far as imagining literary forecasts, turning cultural history into a nomothetic science capable of predicting the success of a best-seller. This is what Jodie Archer (editor) and Matthew L. Jockers (a specialist in digital humanities) propose in *The Bestseller Code: Anatomy of the Blockbuster Novel* (2016), where they assert their ability to predict the success of a novel before publication by analyzing its content, according to a multifactorial model of machine reading. After advanced statistical methods and the emergence of a graphic knowledge that extended (and potentially objectify) the work of historians in different ways, this perspective suggests transforming cultural knowledge even more radically, reducing it to a skillful strategy to launch a machine on a track and interpret the results. To be sure, good reasons exist to remain skeptical and remark that the machine only works with data that it receives, making AI approaches deeply dependent upon theoretical and interpretive choices and frameworks. Still, it would be unwise to disregard the many ways in which artificial intelligence proposes epistemologically disruptive methods capable of profoundly modifying the modalities of demonstration and the very nature of cultural knowledge.

2. Network Analysis

Discussing the intersection between artificial intelligence and network analysis is a complicated task, because the extent of such intersection depends largely on how broadly the two fields are conceived. Network analysis, *stricto sensu*, is the use of techniques derived from graph mathematics to study relational phenomena—that is, composed by a multiplicity of elements considered by their mutual relations rather than by their individual features.[20] Network analysis is a form of topological thinking, in the sense that it focuses on the relative position between elements, but one that considers a space that is multidimensional and non-Euclidian.[21] In the last decades, network analysis has enjoyed an impressive success in academic and industrial research and has become one of the most important fields of interdisciplinary collaboration between social and information sciences. This popularity is justified by the growing interest of social research in relational phenomena and is fueled by the increasing availability of relational records collected through digital technologies. As both the Internet and the Web are network technologies based on network protocol, it is not surprising that network formats have progressively acquired a dominant position in data collection and analysis. Complementing the most classic tools of descriptive and inferential statistics, network analysis has become a crucial instrument to deal with the datasets increasing available on social and human phenomena. Networks analysis would not be unfair to claim is the analytical technique most strongly associated with the birth of computational social science.

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[20] Steven Borgatti, Ajay Mehra, D. J. Brass, et al. « Network Analysis in the Social Sciences », *Science*. 13 février 2009, vol.323 no 5916. p. 892-895.

[21] Tommaso Venturini, Anders Munk, et Mathieu Jacomy. « Actor-Network VS Network Analysis VS Digital Networks Are We Talking About the Same Networks? » in David Ribes et Janet Vertesi (eds.). *DigitalSTS: A Handbook and Fieldguide*, Princeton. University Press, 2019.

Tommaso Venturini, Mathieu Jacomy, and Pablo Jensen. What do we see when we look at networks an introduction to visual network analysis and force-directed layouts. *SSRN* https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3378438

While, strictly speaking, network analysis is not a form of artificial intelligence—in the sense that unlike to the latter it is *not* inspired by human cognitive process or intended to mimic human capacity for problem solving—networks are extensively mobilized in both the symbolic and the connectionist branch of AI. Symbolic AI relies heavily on *semantic nets* as formalisms to represent knowledge ontologies and neural networks are one of the flagship techniques of connectionist AI. Yet in both cases, networks are used as support for other computational approaches rather than as full-fledged analytical tool and combination between graph mathematics and AI is still an emerging field.

For the moment, network analysis and artificial intelligence remain separated branches of mathematics and their alliance is based more on the sequential combination than on the unification of the two computational methods. In most cases, a network is turned into a training dataset for machine learning, by considering its nodes as a list of entities with relational features rather than as different components of a unique graph. According to this approach, relational characteristics are first calculated for each of the node in the network through graph mathematics and then used as features of a machine learning algorithm.[22] The extraction of relational features can be carried out in several different ways. The simplest technique consists in exploiting the classic metrics of network analysis, such as connectivity or centrality. More sophisticated solutions employ advanced techniques of *graph embedding* (projecting the graph in a multidimensional space where distances between couples of nodes can be calculated) and of *graph convolutional networks* (allowing the model to learn the dataset features by inspecting each node as well as its neighbours). A particularly popular solution is the "node2vect" algorithm,[23] which draws on random walks (a classic technique of network analysis) to represent each node through its closest neighbours. In this technique, the sequence of nodes encountered by an agent randomly moving through the network is turned into a vector defining the node of departure, similarly to the way in which the word2vect algorithm turns every word of a text in the vectors of the words that are most often used in association with the target word.

The advantages of approaches that stitch together network analysis and artificial intelligence, rather than unifying them is that, once the relational features are extracted through one of the techniques mentioned above, it is possible to analyze them with a variety of AI techniques, choosing the ones that are more relevant according to the research objectives (anomaly detection, predictive analytics, items categorisation, etc.). Another advantage is that, after the relational structures of the graph is turned in a dataset of features, it is easy to combine these relational variables with other categorical or numerical characteristics of the node of the networks, to investigate their association (to examine, for example, how the discipline or the number of publications influence the collaborations in a network of scientific authors).

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[22] Federico Monti, Davide Boscaini, Jonathan Masci, et al. « Geometric deep learning on graphs and manifolds using mixture model CNNs », *Proceedings - 30th IEEE Conference on Computer Vision and Pattern Recognition*, CVPR 2017. 2017, vol.2017-January. p. 5425-5434.

Siddharth Pal, Yuxiao Dong, Bishal Thapa, et al. « Deep learning for network analysis: Problems, approaches and challenges », *Proceedings - IEEE Military Communications Conference MILCOM*. 2016. p. 588-593.

[23] Aditya Grover and Jure Leskovec. « node2vec ». *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. 2016. vol.95.

3. IA and the analysis of images

Beyond the analysis of texts, quantitative data—and networks—, artificial intelligence is renewing the analysis of images. Art history, in particular, is taking advantage of AI algorithms to develop new approaches—or rather to return to its original ambition: to retrace the history and diffusion of "styles," to understand the life of forms and the evolution of motifs. Indeed, art history emerged in the 18th century from the technical possibility of serializing and comparing images, thanks to engraving and "paper museums," and consolidated in the 19th century with the rise of photography.[24] This work of comparison, based on the images themselves, found its theoretical apogee in the "iconology" proposed by Aby Warburg, as early as 1903.[25] According to him, works of art embed the collective desires and expectations, the *Pathosformel*: studying the circulation of these *Pathosformeln* thus informs about the state of societies, mythologies and aspirations. In order to implement this "modern science of art" (*Kunstwissenschaft*), Aby Warburg relied technically on large panels on which he placed photographs of works of art, grouped according to similar motifs and visual references. Nevertheless, Warburg's iconology was too Promethean a project to be feasible because of the inability to study very large corpora of images: art historians gradually abandoned this ambition in favor of monograph studies or a text-centered approach to the reception of images.[26]

New technical advances allow achieving Warburg's ambition. On the one hand, recent datasets of annotated images have been compiled thanks to the advances of scanning systems, making "Big Visual Data" available to art historians. For instance, regarding the Renaissance (Warburg's preferred period) the Web Gallery of Art, a searchable database of European fine arts and architecture, currently contains over 48,600 reproductions,[27] and the photo-library of the Giorgio Cini Foundation in Venice has about 1 million digitized photos of European artworks.[28] The Google Art project also gives access to a large collection of images, but mainly from American museums with poor coverage of the Renaissance.[29] On the other hand, since 2012, new artificial intelligence algorithms of "computer vision" made possible to formally analyze these images, to compare and to group them according to similar patterns.[30] As a matter of fact, Deep Learning and Convolutional Neural Networks enable to identify structural and compositional similarities between images at different scales, from general patterns in the overall image to smaller-scale details.[31]

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[24] Pascal Griener, *La république de l'œil. L'expérience de l'art au siècle des Lumières*, Paris, Odile Jacob, 2010.

[25] Roland Recht, « L'iconologie avant Warburg », *Images Re-vues* [En ligne], Hors-série 4 | 2013, http://journals.openedition.org/imagesrevues/2898, accessed June 11, 2020.

[26] Béatrice Joyeux-Prunel, « Visual Contagions, the Art Historian, and the Digital Strategies to Work on Them », *Artl@s Bulletin* 8, no. 3 (2019): Article 8, p. 131, https://docs.lib.purdue.edu/artlas/vol8/iss3/8/, accessed June 11, 2020.

[27] https://www.wga.hu, accessed June 11, 2020.

[28] https://www.cini.it, accessed June 11, 2020.

[29] https://artsandculture.google.com, accessed June 11, 2020.

[30] Alex Krizhevsky, Ilya Sutskever, Geoffrey E. Hinton, "Imagenet classification with deep convolutional neural networks" *in Advances in Neural Information Processing Systems*, 2012, pp. 1097-1105.

[31] Benoît Seguin, Carlotta Striolo, Isabella diLenardo and Frédéric Kaplan, "Visual link retrieval in a database of paintings", in *Lecture Notes in Computer Science*, vol 9913. Springer, Cham, 2016.

These “computer vision” techniques spurred notable advances in art history. From 2015 through 2019, the Replica international project led by the DHLAB at the EPFL (Lausanne, Switzerland) in partnership with the Giorgio Cini Foundation in Venice and Factum Arte in Madrid, managed to design a search engine for the exploration of artistic collections. Developed by Benoît Seguin, this navigation system allows exploring connections between some 330,000 documents from the photo-collection of the Cini, and helps researchers in identifying visual links.[32] This visualization takes the form of a network of images: the more similar, in terms of shapes, forms or motifs, the closer in the network—and vice versa.[33] The search engine constitutes a new tool to detect visual similarities in artistic compositions, and offers visual panels similar to Warburg’s, but on a much larger corpus of images. Another international project uses computer vision as a tool to detect motifs that the human eye might have overlooked. Developed by Mathieu Aubry at Ecole des Ponts Paris Tech, in France, the EnHerit algorithm (Enhancing Heritage Image Databases) identifies recurring patterns across vast corpora of heterogeneous images.[34]

Thanks to artificial intelligence algorithms, it is thus possible to renew one of the founding ambitions of iconology, i.e. to identify visual similarities between images, diffusion of patterns or styles. Nevertheless, computer vision cannot replace human vision since it is up to the art historian to constitute the corpus of images, to verify their relevance and, above all, to interpret the visual links between works of art.

III. AI as a societal issue

The social sciences and the humanities are directly confronted to the many societal issues at stake with AI. They aim to study in an interdisciplinary manner the ways in which artificial intelligence is changing society: from facial recognition to connected objects, from robotics, to human-computer interaction, from decision support to massive data, from social web platforms to the rise of micro-work, AI is transforming all sectors of collective life relentlessly extending to commerce and consumption, health and labor, public and personal life. These developments pose considerable problems of economic, geographical and environmental impact, protection of private data, legal responsibility, control of possible ethnic and gender bias, explicability and traceability. These are all societal issues that need to be reformulated as research questions and tackled in collaboration with researchers reflecting from different disciplines about the challenges of morally and socially responsible AI tools and methods.

1. Organizational and political issues

While much has been written about the changes that AI encourages in the epistemic posture of humanities and the social sciences and about the ethical and political risks connected to it,

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[32] Benoit Seguin, “The Replica Project: Building a visual search engine for art historians”, ACM Crossroads24(3), 24-29, 2018.

[33] Benoît Seguin, *Making large art historical photo archives searchable*, PhD, Ecole polytechnique fédérale de Lausanne (supervised by Frédéric Kablan and Isabella diLenardo), 2018, https://infoscience.epfl.ch/record/261212, accessed June 11, 2020.

[34] Shiry Ginosar, Xi Shen, Karan Dwivedi, Elizabeth Honig and Mathieu Aubry, “The Burgeoning Computer-Art Symbiosis. Computers help us understand art. Art helps us teach computers”, *XRDS: Crossroads, The ACM Magazine for Students – Computers and Art archive*, Volume 24, Issue 3, Spring 2018, pp. 30-33, https://dl.acm.org/doi/pdf/10.1145/3186655, accessed June 11, 2020.

less attention has been devoted to the more mundane, yet equally important, transformations taking place in day-to-day research practices.[35] Even when this subject is addressed, it is often to oppose the caricature of traditional scholars working in the isolation of their library, with little more than their intellect and a notepad, to the equally caricatural image of an interdisciplinary laboratory where computer scientists and engineers work hand in hand with social and human researchers collaborating around complex pieces of computing machinery. While it is well-known that information and cognitive sciences have a long interdisciplinary tradition,[36] which can only be amplified by their application to human and social topics,[37] it is misleading to present this research as more collective or more intensively equipped than its traditional counterpart.

Research in large teams and with massive equipment has always existed in the humanities and the social sciences. Libraries and archives, for instance, are extremely vast and sophisticated pieces of intellectual technologies, whose development span through decades and required the collaboration of hundreds and often thousands of scholars. Similarly, social statistics have always mobilised armies of pollsters, data cleaners and analysts;[38] geography could have not developed without the coordination of a multitude of surveyors, cartographers and map designers;[39] and linguistics has always relied on vast collections of speech and writing records. Even anthropology, which often presented as a solitary discipline based on direct and unmediated immersion, has always made extensive use of collective archives of material culture items and field notes.

Conversely and differently from commonplace ideas, digital humanities and social sciences are not always collective enterprises. In fact, the growing availability of datasets, offered by the development of open data and by the platform economy, has allowed quantitative research to be carried out at in individual level. Likewise, the increasing calculation capacities offered by ordinary personal computers and the large number of open-source tools and scripts

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[35] Lucy Suchman, and R. H. Trigg. “Artificial Intelligence as Craftwork.” In *Learning in Doing: Social, Cognitive, and Computational Perspectives. Understanding Practice: Perspectives on Activity and Context*, Cambridge: University Press, 1993, pp. 144–78.

Adrian Mackenzie, *Machine Learners: Archaeology of a Data Practice*. Cambridge Mass. MIT Press. 2017.

[36] Saracevic, Tefko. "Interdisciplinary nature of information science." *Ciência da informação* 24.1 (1995): 36-41.

Paul Thagard,. « Being Interdisciplinary: Trading Zones in Cognitive Science » in Sharon J. Derry, Christian D. Schunn et Morton Ann Gernsbacher (eds.). *Interdisciplinary Collaboration: An Emerging Cognitive Science*. Mahwa, New Jersey. Erlbaum. 2005, pp. 317-339.

David Ribes, Andrew S. Hoffman, Steven C. Slota, and Geoffrey C Bowker. “The logic of domains”, *Social Studies of Science*. 2019, vol.49 no 3. p. 281-309.

[37] Steven Woolgar. “Why not a Sociology of Machine? The Case of Sociology and Artificial Intelligence”, *Sociology*. 1985, vol.19 no 4. p. 557-572.

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available for reuse and adaptation has allowed researchers to embark on a solitary project of data analysis with results that are often as rich and interesting as those of more established research institutions.

In fact, if digital technologies have changed something to research practices, it is rather the way in which they have softened the boundaries of traditional academic institutions, allowing researchers to collaborate in loser but broader networks. This, of course, is connected to the way in which digital media facilitate communication and transfer of information over long distance, but it also depends more specifically on the progressive standardisation of data infrastructure. Consolidating around a limited amount of data formats and programming languages, the development of computer programming brought about a quasi-universal language for exchanging research records and analytic techniques. Today, no matter the type of fieldwork or style of investigation, research records are stored in the same CVS files and databases and can be manipulated with the same languages (R, Python, C++ and a handful of others). This standardization allows scholars from all disciplines to pick from growing catalogues of freely availability scripts for data cleaning and analysis. This is particularly true for the techniques of artificial intelligence which most often enter the humanities and social sciences conveniently packaged as off-the-shelf modules and libraries.[40] Such a standardized architecture has greatly reduced the barriers to advanced computation techniques, allowing an increasing number of scholars from an increasing diversity of backgrounds to access to the state of the art of machine learning. While this may increase the risk of AI techniques being used as black boxes with little understanding of their inner workings,[41] it also creates the potential for even greater exchange and collaboration across disciplinary frontiers.

This erosion of traditional disciplinary boundaries has taken place not only within the academia, but also and more crucially between academic and industrial research.[42] Neural networks and deep learning, much more than most other computing techniques, have been developed outside universities and research institutions, and found their main developers and sponsors in the corporations of the digital economy.[43] In the field of engineering and computer sciences, universities have long learned to compete with companies to attract talented developers and to advance the frontiers of data science. A similar dynamic of collaboration and competition is not beginning to affect study of human and social phenomena.[44] This is hardly surprising, after all an increasing portion of the data and the techniques exploited by digital humanities and computational social sciences comes from internet companies and

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data-intensive corporations—a situation that opens new potential, but also creates new challenges for public academic research.