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MODELLING THE PAST. LOGICS, SEMANTICS AND APPLICATIONS OF NEURAL COMPUTING IN ARCHAEOLOGY

1. Introduction

The study of complex archaeological systems through the new Artificial Intelligence (AI) aims to evaluate the historical and cultural meaning of the relationships between records of the past as an essentially human construction and/or interpretation. This approach is inspired by the epistemic perspective of *Analytical Archaeology* (Clarke 1968) and of *Computational Archaeology* (Doran, Hodson 1975; Orton 1980; Barceló, Bogdanovic 2015), but updates it on the basis of the progress which neural computing has made in simulating the logics and semantics that regulate memory, orientation, classification and mapping of the historical, geographical, archaeological and anthropological contexts (Ramazzotti 2010).

Modelling and simulating the contexts of the past by integrated parallel distributed processing (McClelland, Rumelhart 1986) and through artificial adaptive systems (Ramazzotti 2014) must make use of precise encoding of documents. It takes on an important role in empirical research only when the machine learning results produced become the hyper-surface of a network membrane to continue, update, refine or open the analysis (Ramazzotti 2016).

However, the proposal to study the dynamic and systemic complexity of ancient cultures through neural computing is based on the assumption that their systemic complexity can be approached by advanced technology, mathematically simulating the complexity of intelligence. A new approach is thus founded on a sort of theorem facing a dilemma (Fig. 1): either this theorem must be ignored or computers must be used to assist with their proofs (Bundy 2011).

2. Modelling the past

Analyses and methods which use automated reasoning are "modelling the past" by applying logical inferences to display and predict the results of archaeological research. More recently, it has been pointed out that comparative, inductive, deductive and abductive inferences can be explained by a single cognition process (Hayes *et al.* 2018). Neural computing based on physics and neurobiological research can thus be considered as advanced instruments adapted to simulate cognitive logical inferences, although it has been highlighted that no automated reasoning program can be universal, in the sense of deciding for any set of inference rules and axioms (Pessa 1992).

Within the Humanities, the observations of statistical, mathematical, economic, and geographical relationships processed for a given body of data

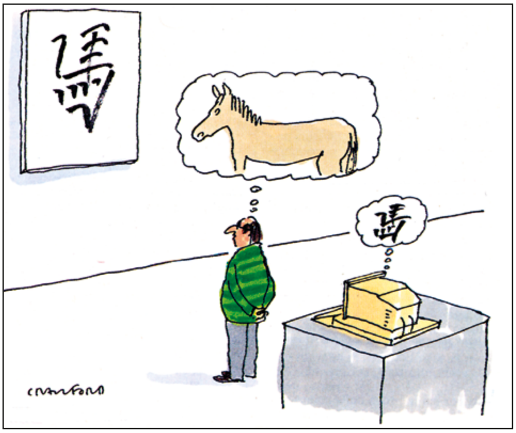

Fig. 1 – Searle wants to demonstrate that no computer programs are formal (syntactic), while the human mind has semantic abilities (Searle 1992, 7, fig. 2).

are represented by matrices, histograms and hierarchical diagrams. They perform the dual purpose of spatializing and structuring the values, percentages, trends and intersections between a limited number of variables. Therefore, these graphs are already models that summarize repeated observations across multiple cases as a result expressed through frequencies, whose different variation and intensity always constitute a degree of (cultural) intentionality (Billard, Diday 2006).

Cultural intentionality in realizing a given production of artefacts presupposes the concept of "type" as a principle, a finite, planned entity expressed by the intentional correlation of different attributes and resulting axioms. Each hidden organization of attributes will define the characteristics of a type; multiple types will define, in turn, the characteristics of a class, and a class the "intentional" product of a culture. The analyses first used by Analytical Archaeology to classify attributes, types and classes of a given culture have been manifold, extremely varied and more sophisticated, the greater the variability of the systems observed (Shennan 2006).

The necessarily accelerating increase in homogeneity of classes and the presence of documents with strongly variable attributes (many of which shared by other artefacts, but none necessary or sufficient to distinguish or characterize them) was incorporated into the genetic concept of "polythetic groups" (Dalton 1981). This is key, because it gave rise to specific research on the most suitable tools to highlight the similarities and differences that could structure composite and/or highly specialized anthropological and archaeological cultures, intended as biological organisms.

Recognition of these qualities (analogies and differences) in the material and visual culture follows the psychological research intended to apply those methods to isolate such essential functions of the cognitive process. In the earliest cumulative analyses, which studied the growth of the level of technology in the same manner as the evolutionary process, the percentages of artefact types were even associated with cranial capacities to explain the presumed symmetry between the growth in functional complexity of a given implement and man's evolutionary growth.

This was essentially understood as adaptive growth, which was due to the necessary acquisition of technological experiences (Leroi-Gourhan 1977). In the same way, the multivariate analysis introduced by the New Archaeology to investigate the systemic complexity of cultures (Binford 1965) supported the methods of Cluster Analysis, Factor Analysis, Multidimensional Scaling Analysis, Fuzzy Clustering and Principal Component Analysis intended to group parts of the data into clusters. This approach was aimed at making future comparative exploration more precise and at identifying its unique and irreducible associative root (Baxter 2009; Shadmehr, Mostafaei 2016; Martino, Martino 2018).

This attempt to trace the origin of the class in order to redesign its relational structure was equivalent to the first experiments performed in analytical psychology to outline the human ability to structure reality into "similar" and "different". The very first studies applying differential logic to understand intelligence gave rise to the suggestion to use techniques such as Correspondence Analysis to reduce the high level of variability of cultural traits into a limited and more controllable number of factors (Sternberg 1985; Kurta, Kurta 2011).

3. Computational neurosciences and archaeology

At the end of the 1980's, numerous studies attempted to understand complexity as no longer external to man and the subject of our predominantly applicative research, but rather as a living expression of our intelligence, our mnemonic, perceptive and learning capacity (Fig. 2). In this sense, complexity was almost removed from the undisputed supremacy of external interpretation, to be analyzed through mechanical and linear systems, and became the subject of specific research which aimed to trace man's cognitive and semantic capacities to create it (Ramazzotti 2013).

The analogy between cultural complexity and the complexity of intelligence then gave rise to a new system of theoretical knowledge, methods and applications linking archaeological research to the new AI (data mining, deep learning, machine learning). Theories, methods and applications already in use identify a completely new world of Archaeology, such as Cognitive Archaeology in slightly different ways (Gardin 1996; Malafouris, Renfrew

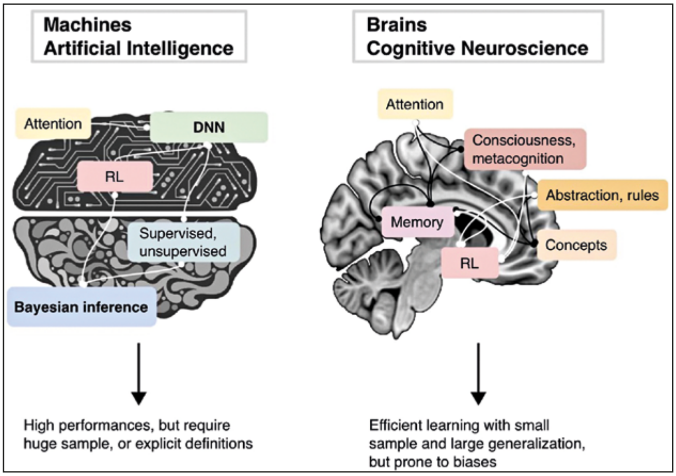

Fig. 2 – Schematic solutions to complex problems in AI and nature (brains). Higher cognitive functions continuously interact between them and with reinforcement learning to drive generalization and learning from small sample (Cortese, De Martino, Kawato 2019, 134, fig. 1).

2010). It is, however, a contemporary approach to investigate past cultures as complex organisms through connectionist formal methods (Elman, Rumelhart 1989). One of the most advanced connectionist formal methods in Natural Computing is the so-called Artificial Neural Networks (ANNs), morphologically structured as multilayer nets replacing neural connections (Buscema, Tustle 2013; Londei 2014) and Deep Neural Networks (DNNs), providing fundamental insights into how populations of neurons collectively perform computation and cocgnitive processing (Penna *et al.* 2016; Barret *et al.* 2019).

Probably the Natural Computing inspired by the connectionist paradigm of AI could represent the deepest roots of contemporary so-called Network Analysis (NA). Although NA is not properly a machine learning process, it is based on multidimensional social networks (Berlingerio *et al.* 2013) and mainly applied as a visual method to display network patterns in the relational phenomena of landscape archaeology (Brughmans 2013; Brughmans, Brandes 2017). While we certainly cannot debate the possibility to artificially recreate intelligence (Searle 1992), it is equally evident that many models emulate and quite clearly come close to some segments of the cognitive process (Fig. 3), such as memorization, classification and learning (Kozme *et al.* 2018; Cortese *et al.* 2019). However the complexity of biological neural networks substantially exceeds the complexity of ANNs and DNNs, making it even more challenging to understand the representations they learn.

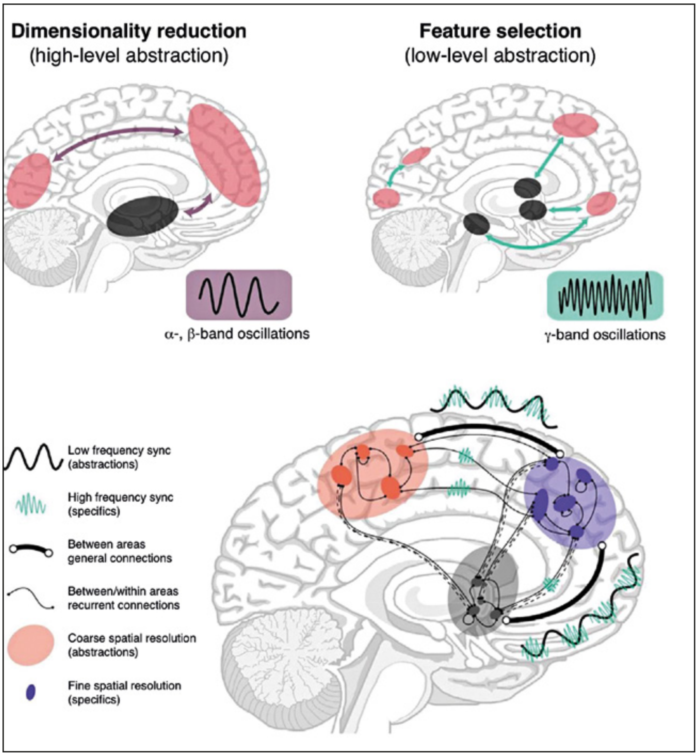

Fig. 3 – Different frequency modes in synchronization of neural activity represent broad and fine dimension reduction and feature selection (Cortese, De Martino, Kawato 2019, 138, fig. 3a).

Segments of the cognitive process are being studied which act in parallel and are able to operate in an integrated manner with today's architectures. However, they only allow the rules that control memory, classification, perception and reflection to be explained. These rules are no longer tracked down in the linear mechanisms of automatic operation, but in the networks which connect the known physical units of the brain, neurons. Transferred to the level of the necessary logical-mathematical identity, these biological entities are defined as nodes, and the synapses that regulate their dynamic functions are called connections. The terms imply another important conversion, that of the biological-cognitive complexity of the world of intelligence into the physical-cognitive complexity of the system of intelligence which, in this manner, favors the processes of analysis experimentation and simulation (Ramazzotti 2014a).

Given these elementary coordinates, it seems clear that simulating the dynamic and complex behavior of highly variable cultural "factors" in networks

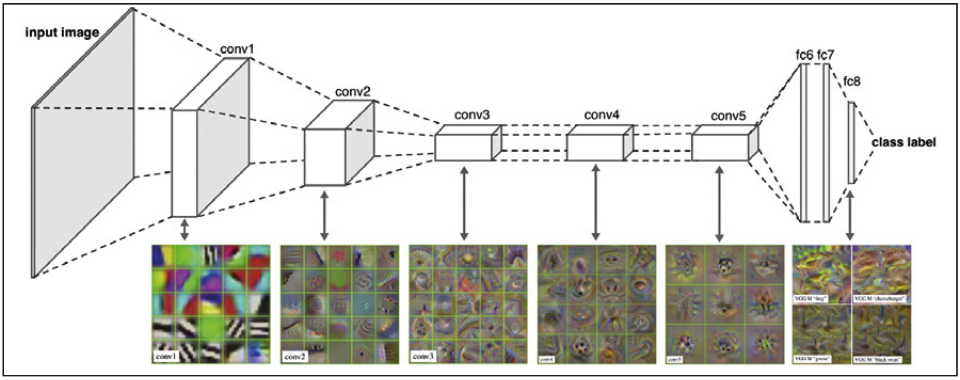

Fig. 4 – Receptive field analysis of neural filters from a DNN illustrates how an input image is progressively processed before finally producing a class label as output (Barret, Morcos, Macke 2019, 56, fig. 1).

means tracking down, selecting and separately recreating a wide variety of functions that associate variables, a wide variety of inferences that control their semantic structure and an equally wide variety of causes that produce their transformation (Ramazzotti 2014b). This perception of functions, inferences and causes that multiply and generate the complex phenomena demands an archaeology concerned with interpreting the past by debating the history of its different perceptions. At the same time, it must trace the complexity of a culture by superseding the classical and dualistic models to display all its extraordinary variability and richness (Ramazzotti 2016).

In this specific sense, the application of AI models to archaeological problems has value. It recreates a possible world of other associations of meaning devoid of sources and dispersed information, it exhibits the nuances and complex interrelations and, furthermore, it helps the interpreter codify other associations that were unforeseen (or hidden). This is a sort of metaphor by which we understand that the complexity of intelligence is related to that of culture (Fig. 4).

4. Neural computing and archaeological and archaeometric case studies

Since the end of the 1990s, matrix encoding of many different archeological contexts has been developed to track down, select, and recreate the functions, inferences, and rules that produced the transformations of cultural systems, understood as multifactorial dynamic processes. The artificial formal networks obtained by such structural and semantic matrix encoding of different contexts were thus thoroughly described, analyzed, simulated and lastly compared. They introduced the most advanced quantitative, qualitative, and symbolic methods inspired by neural computing to simulate cultural systemic complexity in archaeology (Ramazzotti 1999, 2010; Reeler 1999; Zubrow 2003; Bintliff 2005; Baxter 2006).

After 30 years of theoretical and experimental research, this approach maintains a distinct value as a new theoretical approach for the study of the dynamic and systemic cultural complexity, as a new analytical paradigm for computational modeling in archaeology and as an advanced computational method. Neural computing has been tested as an advanced classification method for discriminating between material culture objects, pottery sequences, figurative systems and for encoding other archaeologically-relevant chronological constraints, revealing unforeseen analogies between different clusters and discussing the existence of sub-typologies used to fix the relative chronology (Barceló 1995; Ramazzotti 1997; Barceló, Faura 1999; QingLin Ma *et al.* 2000; Di Ludovico, Ramazzotti 2007; Di Ludovico, Camiz 2014; Viaggiu 2014; Geeraerts *et al.* 2017).

Later, neural computing has been applied to simulate the systemic and dynamic complexity (encoded in different matrixes) of the most ancient settlement processes, integrating data from excavated sites, surface surveys and a mixture of each. Different neural models were proposed as spatial analysis tools to simulate and to investigate the cultural and economic assets of the archaeological settlement systems (Ramazzotti 1999; Zubrow 2003; Deravignone, Macchi 2006; Agapiou, Sarris 2018). Since the end of the 1990s, the neural modeling approach has also analytically challenged the most ambitious hypothesis on the origin of settlement patterns and urban land dynamics. It has explored the possible relationships between the high spatial variability of cities, towns, villages and camps, and the trends of human mobility, suggesting investigations on the socio-political character of the ancient cultural systems' hierarchical organizations (Ramazzotti 2002, 2009; Wu, Silva 2010; Froese, Manzanilla 2018).

In the last twenty years, the neural computing approach has also been applied to encode, classify and display the topology of different kinds of signals (geomagnetic, radar, remote sensing). It has refined the spatial-temporal distribution of the anomalies detected and supported the best non-invasive strategies for archaeological field and landscape activities (Bescoby *et al.* 2006; Opitz, Herrman 2018; Woolf 2018; Caspari, Crespo 2019; Trier *et al.* 2019; Willett 2019). A turning point in neural modelling was the investigation of an empirical analogy between the socio-political and economic complexity of archaeological settlement systems and the dynamic complexity of the biological system. Considering the spatial relations between points (sites) as the nodes and/or cells of a highly interconnected net, the spatial-temporal

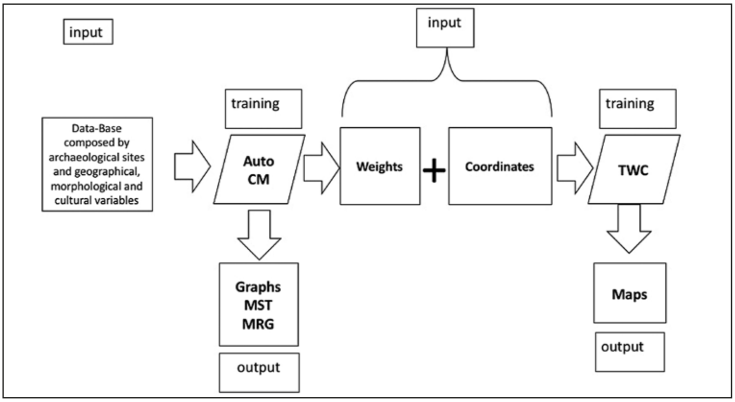

Fig. 5 – The machine learning procedure adopted to process the Mesopotamian Urban Revolution Landscape Data-Base encoded and transposed in a n-dimensional matrix (224 sites for 106 geographical, morphological and cultural variables) (Ramazzotti 2018, 73, fig. 2.4).

nodes (sites) were translated into a network, intended as a membrane activated and transformed by different actions, causes, events and/or agents (Fig. 5).

Each point of the membrane was thus conceived as a geo-referenced archaeological site, and the adaptive network was trained, first through the most advanced generation of Artificial Adaptive Sytems (AAS) and then, the highly sophisticated outputs of the training were optimized, formalized, and displayed through data-mining algorithms in tree-graphs. The graph analysis of the deep learning of the membrane/network was thus tested as a predictive model for locating the possible position of undiscovered monuments and/or sites, and for mapping the dynamic transformations of the settlement processes over time (Ramazzotti 2013b).

This latest experimental and applied research by the Sapienza Laboratory of Analytical Archaeology and Artificial Adaptive Systems (LAA&AAS) has been advanced through a new data-mining machine learning procedure. It has explored the spatial logics and semantics of the most ancient settlement distributions, focusing on the possible topology of settlement patterns and investigating their movement through time (Ramazzotti 2018; Ramazzotti *et al.* 2020).

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ABSTRACT

The study of complex archaeological systems through the new Artificial Intelligence and Natural and Neural Computing is a research project which evaluates the historical meaning of the relationships between records of the past as an essentially human construction. It repeats a strong position of Analytical Archaeology, but updates it on the basis of the progress which neurosciences and physics have made in simulating the principles which regulate memory, orientation, classification and mapping of reality. Modelling and simulating the contexts of the past in integrated, parallel, distributed processing through machine learning methods, must make use of a precise encoding of the documents. It takes on an important role in empirical research only when the results produced become the hyper-surface of a network membrane to continue, update, refine or open the analysis itself. After some 30 years of such theoretical, analytical and experimental research, logics, semantics and applications of neural computing maintain their distinct value as a new theoretical approach for the study of dynamic and systemic cultural complexity. They provide a new analytical paradigm for computational modelling in archaeology and an advanced computational method for pattern recognition in archaeometry.