A CONCEPTUAL FRAMEWORK OF HUMAN-MACHINE INTERACTIONS FOR ENRICHED FUTURES LITERACY

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Abstract

The aim is to develop a conceptual framework of Human-Machine Interaction allowing to generate richer anticipatory assumptions to "use-the-future" thanks to a close collaboration between humans and machines.
"Futures Literacy" (FL), as defined by Riel Miller (2018), is a human capacity generally developed through human interactions only. Here we propose to enrich FL by developing "collective intelligence knowledge creation processes" between humans and a high tech "Data-Analyzer". The idea is to model how a specific human community G in a social organisation S can design such a customized 'evolutive' data-analyzer DA to collaborate in collecting data about the environment and to learn, together, how to analyse them, anticipate situations and develop new responses to the present situation. The DA is being 'processed' to gather data and knowledge, but also to learn how to act itself with specific procedures, or even create new procedures as combinations of known procedures. These rich interactions are expected to allow the couple DA+G becoming Futures Literate.
The methodology relies on the "Memory Evolutive Systems" (MES) (Ehresmann and Vanbremeersch, 2007), a mathematical model for evolutionary multi-scale, multi-agent and multi-temporality complex systems, such as biological, cognitive and social systems. The previous issues are analysed by constructing a large MES modelling S in which G and DA act as 'co-regulators' to form a common 'archetypal pattern' of concepts and processes allowing:

(i) At a given time, formation of a 'macro-landscape' where G and DA cooperate: first by developing a shared view of the situation, making sense of it ('retrospection'), and second by searching for adequate strategies, evaluating them and selecting one ('prospection').

(ii) On the long term, the single and/or cooperative operations between G and DA will be more efficient if they become 'Futures Literate', that is to say if they become able to better 'using-the-future'.

To illustrate our conceptual proposition, we propose two potential applications to health and environmental risk prevention. This illustration suggests how 'use cases' of new Human-Machine Interactions for enriched Futures Literacy may be of interest for policymaking where planning becomes an increasing challenge.

Keywords: Futures Literacy; Anticipation; Human-Machine Interaction; Memory Evolutive Systems

Introduction

Individual or collective (social organisation, enterprise, institution...) decision-making processes and actions depend on the way people sense and make sense of the world around them and its complexity. This process is enhanced if they acquire the capacity to use-the-future (which does not yet exist) in the present thanks to the development of a variety of anticipatory assumptions on this future.
The Futures Literacy Framework (UNESCO FL-project, R. Miller, 2018) consists of developing this capacity for human individuals through 'collective intelligence knowledge creation processes', in particular thanks to the creation of innovative "knowledge laboratories" named "FL-laboratories" (FLL or FLL-N, the N meaning 'novelty'). These are a kind of 'participative laboratories' which comprise more or less heterogeneous people, including experts, facilitators and non-expert users, to debate on some projects in relation with public policies (Michialino & Cowdroy, 2002), education, health policies (Picard & al., 2017), co-design and so on. Several examples ("study cases") of FLL and FLL-N are described in Part II of the book "Transforming the Future" (Miller, 2018). As it is explained in

this book, because of practicality conditions, these FLL have a short duration (a few days) during which participants of various origins develop "Collective Intelligence Knowledge Creation" (CIKC) processes to learn to use-the-future and thus to become Futures Literate thanks to a process allowing the recognition of different kinds of Anticipatory Assumptions.

This paper can be seen as a sequel of Chapter 3 of the above book. Its aim is to enrich the FL framework by defining a notion of Futures Literacy for a social organisation (such as a company, a policy, education or health institution, an association...). Such an organisation is evolutionary with some persistence during which it varies through changes of different natures in its composition, structure and functioning. To ensure a kind of permanence in spite of changes, we develop a conceptual framework of Human-Machine-Interaction allowing a close collaboration between a specific execution subsystem G and a customized 'evolutive' high-tech machine named *Data-Analyzer* (DA). This DA is processed not only to gather and memorize data about the environment, the work done and the work to do, the problems which arise, but also to develop common deep learning making CIKC processes possible for G. Thus, the couple DA+G can generate rich anticipatory assumptions to use-the-future, for instance for risk prevention, becoming Futures Literate over time. Let us remark that this functioning is different from traditional views of participative laboratories of any kind, which have rather been low-tech project-based organisations thus far.
To do so, we rely on the Memory Evolutive Systems (MES) methodology, already used for developing FL in Chapter 3 of the above book. Using this framework, the idea will be to show how DA allows a group G of people acting as a co-regulator to develop stronger CIKC by forming a particular 'Archetypal Pattern' consisting of knowledge shared by the members of G, making explicit some of their tacit assumptions even up to some emotions, eventually leading to an enriched way of acting together by designing 'complex procedures'. As a whole, thanks to the different characteristics of DA and its large database, the couple DA+G can develop new anticipatory assumptions that G alone would not have thought of.
After describing our methodological approach, we develop our conceptual framework and conclude with implications and suggestions for policy making.

Methodological approach

Our approach relies on the *Memory Evolutive Systems* (MES). Introduced by Ehresmann & Vanbremeersch (1987, 2007), the MES propose a mathematical methodology (based on Category Theory coupled with Dynamic Systems) for studying 'complex' evolutionary and adaptive systems such as biological, social and cognitive systems. Such systems have: (i) a tangled hierarchy of complexity levels with multifaceted components; (ii) a multi-agent multi-temporal self-organisation with a network of local *co-regulators*, each operating at its own rhythm with the help of: (iii) a flexible *memory* allowing for self-repair and adaptation to changes. MES do not describe the invariant structure of the system but give a 'dynamic model' sizing up the system in its becoming, with the variation over time of its components and their interrelations, some disappearing while new ones may appear.

1. Brief recalls on MES

In this section 1, we describe the MES H associated to a social organisation S having the above properties and we recall MES main properties; in the following section 2 we explain how to connect it to a high-tech Data-Analyzer to develop rich human-machine interactions.

1.1. *MES* H *associated to* S
The system S has interacting components of different natures: (i) individuals and a hierarchy of groups of interacting individuals; (ii) material components such as artifacts, computers, machines, including the Data-Analyzer DA to be implemented; (iii) memory components such

as contextual data, conceptual and procedural knowledge, algorithms, various memories, and also unconscious or implicit knowledge such as pure practices, heuristics, values of different kinds, even affects and emotions.
The components and the links through which they can communicate are dynamic entities whose successive states during their 'life' can depend on some physical attributes (e.g. activity at a given time, propagation delay and strength of a link,...).

The *configuration of* S at a time t consists of the states at t of components and links between them which exist at that time. In the MES H modelling S, it is represented by a category Ht which has for objects the states of the components existing at t, and for morphisms the states of the links between them. Over time, there are 2 kinds of change for configurations: (i) dynamic changes of state of the components and links existing at t, for instance imposed by energetic constraints; and (ii) structural changes leading to the possible loss or addition of some components or links. In H, the change of configuration, or *transition*, from t to t' > t is modelled by a *partial functor* from Ht to Ht', defined on the components and links at t which still exist at t', which maps their state at t on their new state at t'. The different categories Ht and the transition functors connecting them form an *Evolutive System.*

1.2. *The hierarchical structure*
The system S has a *compositional hierarchy.* It means that the components are distributed into a finite number of *complexity levels*, verifying the condition: at a time t, a component C of level n+1 admits at least one internal decomposition into a pattern of interacting components of levels ≤ n which C 'combines' so that C alone has the same operational role that P acting collectively. [In categorical terms, it means that C is the *colimit* (or inductive limit, Kan, 1958) of P.] Over time, the decomposition P of C may vary progressively, and eventually have completely disappeared after some time while C still persists. C acts as a "Janus": it is 'simple' vs. higher levels, and 'complex' vs. lower levels. Successive decompositions of C down to level 0 are named *ramifications* of C. The *order of complexity* of C is the smallest length of a ramification of C; it is less or equal to the level of C. Reductionism would mean that the complexity order of C is always 0 (at level 0) or 1.

[Formally, a *pattern* (or diagram) P in a category consists of a family of objects P_i and some morphisms between them. A *cone* (modelling a *collective link*) from P to C is a family of morphisms s_i from P_i to C well correlated by the morphisms distinguished in P. The pattern P admits a *colimit* cP if there is a cone from P to cP through which any cone from P to C factors uniquely. A category is *hierarchical* if the class of its objects is partitioned into a finite number of *complexity levels*, so that each object C of level *n*+1 is the colimit of at least one pattern P with each P_i of level < n+1; such a P is called a *lower levels decomposition* of C. A *Hierarchical Evolutive System* is an Evolutive System in which the configurations are hierarchical categories.]

1.3. *The Multiplicity Principle at the basis of flexibility*
An important property of the system S is a 'flexible redundancy' which generalizes the degeneracy property of biological systems (Edelman & Gally, 2001). It asserts the existence of components C which are *multifaceted*, in the sense that they can operate through [formally, are the colimit of] several structurally different non-connected lower levels decompositions and switch between them; over time, they take their own individuation independent from their lower levels constituents. In the associated MES H, this property is called the *Multiplicity Principle* (MP) and it allows for the existence, besides *simple links* which bind clusters of lower level links, of *complex links* which are composites of simple links binding non-adjacent clusters. For S, the emergence of complex links is at the root of "*change in the conditions of change"* (Popper).

MP gives flexibility to the system in particular to develop a robust though flexible memory in which a component (named *record*) can be recalled through any of its different ramifications, providing plasticity over time to adapt to environmental changes.

1.4. *The De/Complexification process leading to emergence*

As stated in 1.1, the change of configuration from t to t' is both due to dynamical changes of states and to structural changes. The structural changes correspond to the four "standard transformations" singled out by Thom (1975): Birth, Death, Scission, Confluence. In the social organisation S, they correspond to: introduction of a new component (e.g. recruitment of a new employee), or rejection of an existing one, decomposition or formation of an interactive group of components. In the configuration category Ht of the associated MES, they correspond to the following operations: 'adding' external elements, 'suppressing' or 'decomposing' some components, 'combining' a given pattern P into a new emerging component [due to become the colimit of P]. Given a procedure Pr with objectives of the above kinds on the category Ht, the de/*complexification process* for Pr consists in constructing a category H' in which these objectives are optimally satisfied. In (Ehresmann & Vanbremeersch, 2007), H' has been explicitly constructed and its 'categorical' construction gives conditions on Pr for the validity of the following

Emergence Theorem. *For specific procedures, the de/complexification process leads to the emergence of (multifaceted) components of increasing complexity orders, connected by complex links which render unpredictable the result of iterated de/complexifications.*

Warning. The 'categorical' construction of H' does not explicitly take into account the dynamic attributes of the components and links. For H' to become the effective configuration of the system at a later time, it must be compatible with the different dynamic and physical constraints imposed by these attributes.

1.5. *The Memory*

The social organisation S develops a flexible long-term *memory*. In the MES associated to S, the memory is modelled by a hierarchical evolutive subsystem whose components are named *records*. A multifaceted record takes its own individuation over time and can be recalled through its different ramifications. This memory develops over time through successive de/complexifications and it so acquires records of increasing complexity orders (cf. Emergence Theorem which implies that iterated de/complexification processes give a categorical approach to 'Deep Learning').

In the memory, we distinguish different types of records, among them:

(i) A *procedural memory* whose records memorize some kind of action allowing certain objectives to be achieved; such a procedural record Pr is connected by 'command' links to a pattern of effectors through which it can be realized; for instance, a procedure for modifying dynamic attributes of a component can be realized by an algorithm computing the changes to be done. If Pr has formerly been applied with success in a specific situation, it can exist an *activator link* from the record of the situation to Pr.

(ii) A *semantic memory* which gradually develops through the classification of records into invariance classes represented by a specific concept (Ehresmann & Vanbremeersch, 2007).

1.6. *The local and global dynamics*

The social organisation S acts as a multi-agent self-organized system and its dynamics is modulated by the cooperation and/or competition between its processing agents. These agents, named *co-regulators*, can be simple individuals or formal groups of interacting people and/or machines; for instance the Data-Analyzer acts as a co-regulator. The overall dynamics weaves the different internal local dynamics of the co-regulators. In the associated MES H, a co-regulator is modelled by an evolutive subsystem.

Each co-regulator CR has its own function, its differential access to the memory, in particular to recall the procedures related to its function, and it acts stepwise at its own rhythm; the rhythms of the co-regulators can be very different. A step of CR from t to t' is divided in 3 more or less overlapping phases:

(i) Formation of the *landscape of* CR at t which collects the partial information on the system and its environment obtained via the active links arriving to CR during the step from other parts of the system, e.g. the memory or other co-regulators. This information is analyzed to make sense of it. [In H, the landscape is modelled by an Evolutive System having these active links for components.]

(ii) Using the memory, a procedure Pr is selected through the landscape; it is not realized on the landscape but by activation of its commands to the effectors of Pr.

(iii) This starts a dynamical process (eventually leading to differential equations) whose result will be evaluated at the beginning of the next step; if the objectives of Pr are not attained, in particular if Pr is not compatible with dynamic and temporal constraints, there is a *fracture* for CR.

At a given time, the various co-regulators may send conflicting commands to effectors. The global dynamic results from an 'interplay' among them, and it may cause a fracture to some of them. While the local dynamics can be computable, the interplay between co-regulators renders the global dynamic unpredictable.

2. FL-MES to study human-machine-interactions

Here we define the concept of a FL-MES to represent a continuous situation in which a social organisation S collectively develops an "emergent and evolving" (Miller, 2018) Futures Literacy capacity thanks to an internal evolutive high-tech *Data-Analyzer* (DA), able to memorize the different data and operations and, through rich human-machine interactions, to act as a partner in collaborative decision-taking and action 'using-the-future".

The DA is equipped with: (i) different kinds of 'receptors' (sensors, users' interface,...) and 'effectors' to communicate both ways with the system and its environment; (ii) a central processing unit to analyse and treat information; (iii) a multi-level 'memory'. It is 'evolutive' in the sense that Its material conformation may be modified over time to improve its performances.

In the MES representing S, DA is modelled by a co-regulator still named DA, able to accomplish the following operations, either alone or through interactions with higher co-regulators of the system to form a collaborative work system:

(i) Through its receptors (e.g. sensors), it continuously collects in its landscape material and behavioural data coming from the system and its environment, in particular from different co-regulators of the system. It ensures their persistence (meaning that they outlive the process that created them), by storing them in its memory and (by evolutionary computing) organizes this memory in a "relational database".

(ii) It cooperates with higher co-regulators to develop the global memory and organize it into multi-levels up to the formation of a conceptual level (in the semantic memory) and of more complex procedures and procepts (in the procedural memory).

(iii) It helps decision-making using-the-future by interacting with higher co-regulators. Thus the MES also acts as a "collaborative decision-making system" (Zarate, 2013), though, eventually DA can itself select already known procedures and realize them (by activation of their effectors).

Results and discussion

1. **Modelling and classifying Anticipatory Assumptions**

For a system, Futures Literacy depends on the development of a rich variety of *Anticipatory Assumptions* (AA) which "are the fundamental descriptive and analytical building blocks for understanding FL and using-the-future" (Miller, 2018, p. 24). These AAs can be explicit (conscious or not for human groups) or only tacit. We will show how the human-machine interactions with DA can help transform tacit AAs into explicit ones.

In the MES H representing a social organisation S (including or not a Data-Analyzer), an AA for a co-regulator CR (at a given time t) corresponds to the choice of a specific procedure Pr on its landscape and evaluation of its expected result (if the realization of Pr succeeds).

In (Miller, 2018, Chapter 2) R. Miller has classified AAs in different groups. Here we adapt this classification in our frame.

(i) AAs corresponding to some kind of "repetition" (AA1 and AA3 relative to "General Scalable" methods of knowing for Miller), that search for *an extension of the present in the future*. They correspond to the case where the present situation has already been met, and there is an activator link from its record to a procedural record which had given a satisfying result. Then the AA will consist in activating the same procedure (via the activator link); an example is given by the use of statistics; this represents a kind of "colonization" of the future, impeding real novelty. In case the situation has received different responses in former occurrences, there can be several activator links, and some choice will have to be made among them, leaving some freedom of choice (AA5). In any case, the result of the procedure can be different from the expected one, due to possible not-recognized changes in the situation.

(ii) AAs corresponding to novel futures in answer to the detection of "Specific-Unique" phenomena such as weak signals. They can just rely on preconceived normative futures (AA2 and AA4). Or they can require new procedures leading to the emergence of higher complex objects and links (AA6),

As we are going to show, human-machine interactions render it possible to discover more weak signals and increase the number of procedures the system can form, thus increasing its FL-capacity. Indeed, with its larger and more complex memory, DA makes it possible to form more extended landscapes and discover a richer stock of innovative procedures, whence more AAs.

2. Human-machine interactions in a FL-MES

To simplify, when no confusion can arise, we will not make an explicit distinction between a social organisation S equipped with a Data-Analyzer DA and its associated FL-MES in which DA operates as a co-regulator, either by itself or in coordination with humans.

By itself, DA acts as a co-regulator: at a given time its landscape gathers the information received from its receptors or coming from the memory and other co-regulators. Depending on the number and precision of its receptors, it can distinguish some weak signals (e.g. a small anomaly in the data sent by a sensor), and alert the system. If it had already met a similar experience, it can even select (through an activator link) a procedure used to correct it and activate its effectors. This allows for a quicker answer, possibly avoiding more serious risk, but may need some control to avoid errors or unethical behaviour.

DA also cooperates with an executive group G of humans (acting as a co-regulator) to form a collective decision-making system able to develop more innovative anticipatory assumptions leading to 'novel' futures. In the MES, the 2 co-regulators G and DA and the different links which connect them act as a (macro-)coregulator whose landscape, named the m*acro-landscape* (ML) constitutes their collective working space.
Let us describe how they proceed for: (i) sharing of information and knowledge of different kinds by forming a pattern AG of shared 'G-archetypal' records; (ii) constructing ML with the help of AG and analysing it to make sense of the present situation (*retrospection process)*; (iii) searching for adequate AAs (*prospection process)* and finally reach a consensus decision 'using-the-future'.

In these operations DA does not just operate as a multi-level database but also as an information collector, even able to detect some weak signals, and as an active coordinator. In time, S may improve DA performances by configuring relevant changes (in hardware or software) to address current challenges effectively, for instance by increasing the number, the precision and/or the capacities of the receptors and effectors.
Hereafter we suppose that DA can record voices through hearing devices, memorize them, and process them to infer some personality traits of the speakers such as Dominance or Trustworthiness (Ponsot & al., 2018). It may also detect some primary emotions (e.g., Pleasure, Arousal) from their attitudes and deduce other emotions (using the computational PAD Emotion Model, Zangh & al, 2008).

2.1. *DA helps forming the G-archetypal pattern of G-shared records*

Initially, the members of G have different individual expertise and knowledge. A higher order multifaceted record A, such as a polysemous concept integrating knowledge of different modalities (explicit or not), may have different meanings for two members of G depending on the ramification(s) through which they recall it. Exchanges of information between them to reach a common understanding are perceived by DA receptors and memorized so that DA may store A with all its different ramifications, whence forming a common enriched perspective A* of A accessible to all. A* encompasses the different meanings of A and eventually some tacit knowledge, such as the emotions aroused in the course of the discussion. A* is called a G-*archetypal record.*
These records are connected by loops of strong and fast complex links, which self-maintain their activity for a long time; with these links they form the evolutive G-*Archetypal Pattern* of the group G. [The development of AG is a consequence of the Emergence Theorem.]

2.2. *Construction and analysis of ML*

AG acts as an engine for the construction of the macro-landscape which contains the landscapes of G and DA, interconnects them and extends them. Indeed, the recall by G or DA of a G-archetypal record A* in their landscape first diffuses in AG through archetypal loops, then propagates to lower levels through the unfolding of ramifications and switches between them, thus extending ML. Moreover ML lasts longer due to the self-maintained activation induced by AG.
In ML, current observations and recent events can be related to past more or less similar cases, allowing to sense and make sense of the present situation, its trends and its possible evolution. This *retrospection process* is followed by a *prospection process*, still using the engine role of AG, to search for possible anticipatory assumptions and 'virtually' evaluating their risk of dysfunction, and finally to select one which uses-the-future. Once a consensus decision has been taken, it is memorized by DA together with the rejected dissenting views, as well as its later outcomes, to be of help if a similar situation recurs.

Remark. The above constructions generalize those done in a D-MES (Béjean & Ehresmann, 2015) to model how a group G of humans collaborate. The benefits of introducing DA are the detection of more (even weak) signals and the development of a more efficient collaboration thanks to a larger sharing of (explicit or tacit) knowledge, leading to better 'using-the-future' and increasing Futures Literacy. [These benefits can be measured by comparing AG and ML to the corresponding archetypal pattern and macro-landscape which would be associated to G in the (D-)MES associated to S in case no DA were added.]

Implications and Conclusions

In this paper, using the MES methodology, we have extended the FL framework to a social organisation by introduction of an evolutive high-tech Data-Analyzer. This DA allows its couple DA+G with an executive co-regulator G to become Futures Literate by developing innovative anticipatory assumptions which "push the boundaries of conventional thinking, with the hope of revealing and inventing innovative strategic policy choices " (Miller, 2018, p.111). Let us give 2 potential applications in the domain of risk prevention.

1. Health-Risk prevention in a care-house for fragile persons

In this scenario, the medical staff (physicians and nurses) G trains a high-tech evolutive Data-Analyzer to assemble a large number of medical knowledge and personal data on the residents (collected through non-invasive devices), to analyse them, and to learn, from G, possible treatments and their effects. The FL-MES conceptual framework shows how, together, they can develop creative processes monitoring health risks and, as much as possible, preventing stressing events or reducing them. Once DA has memorized pathological symptoms, it can quickly recognize them, inform the medical team and eventually start an already used adequate treatment. Thus pathologies are recognized and cured more quickly, e.g. preventing dissemination of epidemics.

2. Environmental risk prevention

Authorities and policy makers are ever more confronted with multiple environmental changes which are to be grasped at both a global (e.g. climate, biodiversity) and local scales (e.g. pollution, industrial risks, extreme events). In this scenario, a group G of members of a local environmental public agency S trains a high-tech data-analyzer DA to deal with *environmental information*. The aim is that DA collects various data, analyses them and learns to help G provide rich anticipation assumptions in respect to environmental risks. These data include various measurements on the environment, expert knowledge on it, but also situated first-person data. Indeed, access to information, even though in larger quantity and of better quality, can be relevant only if people become able to *use* it in practice, which implies encompassing the individual and collective experiences of people interacting with their *milieu* (e.g. social practices, situated knowledge, land-use conflicts,...). The FL-MES conceptual framework shows how to sustain rich DA+G human-machine interactions to produce such meaningful environmental information, whence going beyond what is traditionally understood as “environmental data” by the “digital turn”,

In both cases, by providing insights on how to combine multiple sources of data, ranging from scientific measurements to subjective experiential and emotional contents, analyze and use them in order to develop enriched Futures Literacy, our conceptual framework could help decision makers and policy makers in elaborating new ways for preventing various risks for the populations they are in charge of.

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