Toward a cooperative brain: continuing the work with John Taylor

Bruno Apolloni

Abstract—I propose a three-step discussion following a research path shared in part with John Taylor where the leitmotif is to understand the cooperation between thinking agents: the pRAM architecture, the butler paradigm, and the networked intelligence. All three steps comprise keystones of European projects which one of us has coordinated. The principled philosophy is to "start simple and insert progressive complexity". The results I discuss only go as far as the "start simple" point. The final goal is to find a bias that underpins the entire research effort. In this paper I will move within the connectionist paradigm at various scales, the largest being one that encompasses an Internet of Things instantiation.

I. INTRODUCTION

LET us skip in this special paper the canonical thread of "general introduction of the topic"–"framing it in the literature"–"original contribution". Actually, I discuss here some rather heterogeneous topics to be framed in the John Taylor vast bibliography in view of capturing a unifying line of the John’s research and my own, all while saying nothing truly original in principle. Rather, I try to offer this discussion the peculiar perspective of the European projects within which this collaboration has been carried out, and my latest research as well. I refer in particular to the work done (or to be done) within the sphere of the following four projects:

- Novel Neural Networks [1] carried out from 1994 to 1997 within the HUMAN CAPITAL AND MOBILITY framework,
- PHYSTAA (Principled hybrid Systems, Theory and Applications) [2] from 1998 to 2000 within the EC TMR framework,
- ORESTEA (Modular Hybrid Artefacts with Adaptive Functionality) [3] from 2001 to 2003 within the EC FP5 framework, and
- SOCIAL&SMART(Social housekeeping through inter-communicating appliances and shared recipes merged in a pervasive web-services infrastructure – SandS) [4] to be carried out from 2012 to 2014 within the EC FP7 framework.

I develop this discussion along the mentioned steps, respectively in Section II, Section III, Section IV, then end with a short concluding section.

II. THE pRAM ARCHITECTURE

The pRAM (probabilistic random access) model has been introduced by John Taylor [5] in the early 1980s as an essentially conceptual tool to study relationships between thinking units: none other than the rule chain to express the probability \( P(x) \) of a binary string \( X \) through the conditional probabilities of its ordered bits. Namely

\[
P(X) = \alpha(1)^{x_1} (1 - \alpha(1))^{1-x_1} \alpha(x_2(2))^{x_2} (1 - \alpha(x_2(2)))^{1-x_2} \alpha(x_1, x_2(3))^{x_3} \ldots \alpha(x_1, x_2, ..., x_{\nu-1})^{(\nu)} x_{\nu} \left(1 - \alpha(x_1, x_2, ..., x_{\nu-1})\right)^{1-x_{\nu}}
\]

having introduced the set of \( 2^\nu - 1 \) parameters

\[
\{\alpha_{x_1, x_2, ..., x_{\nu-1}(i)} = P(X_i = 1|X_1 = x_1; \ldots; X_{i-1} = x_{i-1}), i = 2, \ldots, \nu\}.
\]

Learning the underlying process that generates the string results in estimating the values \( \alpha_{x_1, x_2, ..., x_{\nu-1}}(i) \) of Bernoulli conditional variables. Thus we may schematise the pRam hardware as in Fig.1 [6]. However, in a more modern vision, we may reinterpret it in the framework of Internet where people are bombarded by an avalanche of information at any time, so that the sole reaction to any piece of information is usually "yes, I like" or "no, I don’t like". This bit is also the typical informative content for a vast part of the knowledge exchanges between members of a social network. Hence, we may basically model the information exchange through a Bernoulli variable of parameter \( \theta \) synthesizing the quality rank of a thematic thread of documents that are supplied by the network. The model we outline is the following.

![Fig. 1. The pRAM architecture](image)

Each document of a given thread is associated to a Boolean value (like/dislike). The web service providing the document itself sends also this association: thus the latter comes from an impartial judge (for instance, the majority of previous readers) so that each member of the social network accepts it as a real observation of the Bernoulli variable describing the quality of the entire thread. In turn, the network members must vote on the thread so that the average of their votes represents the perceived quality score of the thread. The goal is to get real and perceived quality scores to nearly coincide after a relatively short time. We achieve this goal through a simple moving average algorithm, where previous votes are exponentially smoothed and the additional peculiarity that:
each community member affects with a positive coefficient his/her own vote and a negative coefficient the others. This formalizes a healthy distrust of gossipy opinions which may lead to a better final conviction. Technically, the analytical counterpart of the above formalization is the following. At each discrete time $t$, we are supposed to:

- $X(t)$, the observation at time $t$ (the label produced by the web service);
- $\{A_k(t-1), k=1,\ldots,n\}$, a family of estimators of $\theta$ based on the observations up to time $t-1$ (one for each among $n$ community members);
- $Y_{[k]}(t) = \text{Int}(U_k + A_k(t-1))$, the output signal at time $t$ of the model based on observations up to time $t-1$. Here, each $U_k$ is uniformly distributed in $(0,1)$ (and independent of the rest of community activities).

where the estimators update as follows according to the weights $\epsilon_0, \epsilon_1, \epsilon_2$ affecting, respectively the web service evaluation, own label and the ones of other members:

\[
A_k(t) = (1 - \epsilon)A_k(t-1) + \epsilon_0 X(t) + \epsilon_1 Y_{[k]}(t) + \epsilon_2 \sum_{j \neq k} Y_{[j]}(t)
\]

A negative value of $\epsilon_2$ introduces a negative correlation between the votes of the various members (in the role of gossips, hence the name of the method: Learning by Gossips [7]) which reduces the MSE of each gossipy conviction $S_n$. Its asymptotic expression is

\[
E \left[ \left( \bar{S}_n(\infty) - \theta \right)^2 \right] = \frac{1}{n} (n-1)\delta_b + \frac{\delta_a^2}{\delta_b} E[|A_k(\infty) - \theta|^2] + |\delta_b - (n-1)\delta_a^2|\sqrt{\theta(1-\theta)}
\]

where

\[
\delta_a = \epsilon_1 - \epsilon_2; \quad \delta_b = 1 - (1 - \epsilon_0 - n\epsilon_2)^2
\]

entailing the negative asymptote for $\epsilon_2$ approaching $-\epsilon_0/n$ like in fig. 2.

### III. An Electronic Butler Paradigm

Focusing on peer-to-peer interaction between thinking units, in our common materialistic vision of life [8] John and I focused on the interaction between a human and computing unit. The latter is obviously less equipped than the human as for cognitive capabilities, yet sufficiently powerful to base interactions on both verbal and non-verbal signals. Therefore we hypothesize it to be somehow able to interpret the person’s wishes and preferences and, like a butler, take decisions accordingly [9]. So the typical experimental setup of our investigations is like in Fig. 3: a person equipped with a set of biosignal sensors (electrocardiographic, respiration, galvanic skin response and skin temperature signals) engaged in some demanding task, and a companion computer devoted to interpreting the person’s state in a way that is suitable to improve the task success. This research started around year 2000, recognizing the current instances of the affective computing vein [10]. According to MIT medialab team, affective computing is computing that relates to, arises from, or deliberately influences emotion or other affective phenomena [11]. The tightly pragmatic Jon’s approach is captured by the following sentence: In order to achieve affective computing it is necessary to know what is being computed. That is, in order to compute with what would pass for human emotions, it is necessary to have a computational basis for the emotions themselves. What does it mean quantitatively if a human is sad or angry? How is this affective state computed in her/his brain? It is this question, on the very core of the computational nature of the human emotions, which is addressed in this chapter [12].

In addition to some psychological-biased studies aimed at capturing the main parameters describing emotions [13], the main focus of this research was the way of jointly exploiting both symbolic and non symbolic signals, in a framework synthesized in the path from synapses to rules [14]. The goal was very ambitious, so that a vast variety of methods and algorithms where involved and even originally coined. The strongholds were:

1) a new statistical framework, reminiscent of the Fisher approach [15], which proves more suitable for dealing with computational learning problems;

2) a special family of ICA algorithms to extract independent components from an ensemble of signals in terms of Boolean variables – which are more suitable for being processed through symbolic methods. The family is named BICA [16] and the algorithms for extracting these components are based on peculiar neural networks;
3) a symbolic abstraction method for moving from concepts to meta-concepts in a Boolean hypercube. Since we root these methods on the Probably Approximately Correct learning algorithms introduced by Vapnik [17] we named it PACmed(itation) [18];

4) a fuzzy relaxation method to interpolate between the borders of the special rough sets that are generated by the Pacmed algorithm [19].

All these methods have been integrated in a rule fabric that we introduce in [20] to characterize emotional states (angry, sad, pleased, happy and neutral) of people as they emerge from acoustic features of sentences spoken by them.

It is a layered architecture, as shown in Fig. 4, where the left part identifies a neural network that produces symbol assignments from the original signals and the remaining layers are Boolean gate arrays that group these symbols into formulas of increasing structural complexity.

As a major result of the European project ORESTEIA, we used the same rule fabric to identify the rules which distinguish attentive from inattentive states of a driver during a simulated drive [21]. The experimental setup was the one in Fig. 3, while a template output is shown in Fig. 5. It consists of the visual frame seen by the driver sitting in a car-driving-simulator-station coupled with a pair of graphs. The lowermost reports the physical curve parameters (STISIM parameters) recorded by the simulator, denoting car acceleration, braking strength, wheel angle, distance from the center line. The uppermost graph shows two Boolean variables: red bars go up when an attention requiring episode occurs according to some empirical rules of ours; green bars go up when the system detects a heightened state of attention on the part of the driver. The frame refers to the beginning of a foggy tract in the road where due to thick fog the attention of the driver has become keener even though the STISIM parameters have denoted no particular episodes.

IV. A NETWORKED INTELLIGENCE INSTITUTIONALIZATION

As a synthesis between the two above ideas, in the latest project under my coordination (SandS [4]) the networked computing units are precisely people, namely housekeepers who cooperate to automatically produce recipes for their appliances, each one personalized in line with the individual user’s wishes and preferences. Hence, we look again for an electronic butler, whose intelligence however is not concentrated in the local circuits of the single units. Rather it is networked in a very special social network, which we call social network of facts, where profiles and fuzzy feedbacks of users are collected and processed in order to issue a set of instructions directly to the appliances – for instance to wash on my washing machine colored pools without damage to the color and with the resulting pool softness that I like (see Fig. 6).

In an extreme synthesis the project deals with a social network aimed at producing recipes with tools of computational intelligence, to be dispatched to household appliances grouped in the homes through a domestic WLAN. A recipe is a set of scheduled, possibly conditional, instructions (hence a sequence of parameters such as water temperature or soak duration) which completely define the run of an appliance. They are managed by a home middleware (domestic infrastructure) in order to be properly transmitted to the appliance through suitable protocols. The entire contrivance is devised to optimally carry out usual housekeeping tasks through a proper function of house appliances with a minimal intervention on the part of the user. Feedbacks are sent by users and appliances themselves to the network intelligence to close the permanent recipe optimization loop, with offline advises from appliance producers. An electronic board interfaces the single appliances to domestic infrastructure (see Fig. 7)
Apart from challenging architectural and telecommunication problems this social network deserves (actually an advanced Internet of Things [22]), and in spite of the somehow triviality of the tasks to be achieved (such as washing clothes), this framework represents a real arena where granular computing paradigm can be concretely tossed: real fuzzy feedbacks coming from real people (nothing simulated) to solve a well-defined operational problem within a rather fuzzy environment. The favorite tools planned for Networked Intelligence are Case Base Reasoning, neurofuzzy systems and reinforcement learning. At present we are in the very early stages of the project, where the main philosophical option we adopted is a human-centric approach. It entails that the individual person is the final owner of the above information chain, though the systems is transparent to him: i) he just plugs&plays the appliance, ii) enters the network almost automatically and iii) sends feedbacks in the most natural way, i.e. through fuzzy quantifiers. The whole contrivance runs without invasive and costly hardware. Rather, the project is open source (open hardware/open software) thus calling the user for possibly becoming a co-designer of the system itself.

Fig. 8, shows a preliminary mockup we are assessing at the Laboratory for Neural Network (LAREN) of University of Milano to survey the families of problems that must be solved in the project. It is the photo of a washing machine wifi connected to Internet through an interfacing Arduino board, in order to receive recipes and send back status signals. Recipes are washing like the following

<table>
<thead>
<tr>
<th>Washing cycle parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Soak time</td>
</tr>
<tr>
<td>Washing time</td>
</tr>
<tr>
<td>Rinsing time</td>
</tr>
<tr>
<td>Spinning time</td>
</tr>
<tr>
<td>Washing water</td>
</tr>
<tr>
<td>Rinsing water</td>
</tr>
<tr>
<td>Soap kind</td>
</tr>
<tr>
<td>Soap qty</td>
</tr>
<tr>
<td>Soak+washing water temperature</td>
</tr>
<tr>
<td>Washing alternate speed</td>
</tr>
<tr>
<td>Rinsing alternate speed</td>
</tr>
<tr>
<td>Spinner speed</td>
</tr>
</tbody>
</table>

Table I
A TEMPLATE WASHING MACHINE RECIPE.

It is amazing to learn from the Executive Summary of World Robotics 2011 (IFR Statistical Department, 2011) that 2% of the entire world robotic market (including both industrial and personal appliances) was represented in 2010 by the vacuum cleaning robots which were sold in a number of 1.445 million of units for a total of US$ 369 million and around 9 millions of units are forecasted within 2014. Actually, in recent years the favorite investigation field of John Taylor has been consciousness [23], ergo a very high and challenging functionality of the human brain. However, in recent paper of him [8] he conjectured that a model based on biological neural circuits (CODAM) “is the source of the notion of human soul”. In this short note I have tried to partly sum up the John’s idea toward a brain based understanding of mind and soul, in a series of extremely material instances that may reflect on the mentioned success of the vacuum cleaner, concretely fitting the user needs, and on the current
deal of the social network, as a fractal extension of our brain networks. The lead idea is: if we are able to solve the intelligence of tasks that people perform on an everyday basis, then we could be enabled to understand some of the underpinning brain functionalities, consciousness included.

REFERENCES