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TECHNOLOGIES FOR SENSING AND MODELING COLLECTIVE INTELLIGENCE

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Abstract: New technologies, such as smart mobile communication and computing devices, GPS tracking, video surveillance, RFID, web activity logs, etc. offer unprecedented means for automatic sensing and interpretation of a variety of aspects related to human interactions in groups, social networks, organizations, collectivities, or entire societies. It results that it is now possible to design technical systems capable to harness and leverage the collective intelligence. This paper is a brief review of the literature dedicated to this topic, aiming to identify the main approaches used for designing such systems, and to place our own research in this field in a larger context. Besides that, a simple agent based simulation experiment attempts to provide an answer to the question: "Why is Romania different", from the perspective of the (lack of) collective intelligence.

Keywords: Collective intelligence, human stigmergy, wearable sensors, activity recognition, Agent based simulation

1. INTRODUCTION

Back in 1907, the famous Victorian polymath Sir Francis Galton noticed that the average of the estimated values proposed by a group of about 800 competitors trying to guess the weight of an ox was better than any individual guesses. His paper on this topic, published in Nature (Galton, 1907), coined the term "wisdom of the crowd", and the idea that a collectivity can perform better than any of its individual members remains a classic argument in favor of democracy.

Later research showed that the problem of collective intelligence (C.I.) is far more complex than averaging individual opinions or decisions across a group or collectivity. According to Levy (1997), "collective intelligence is a form of universal, distributed intelligence, which arises from the collaboration and competition of many individuals". Heylighen et al. (2013) propose a more restrictive definition, excluding non-human agents: "collective intelligence can be understood as the capacity of a group of people to collaborate in order to achieve goals in a complex context". Wooley et al. (2010) adopted a task oriented approach ("by analogy with individual intelligence, we define a group's collective intelligence (c) as the general ability of the group to perform a wide variety of tasks."), and measured a C.I. quotient for groups according to a methodology similar to that used for computing the individual I.Q. Finally, in (Susnea, 2016) we proposed a more comprehensive definition of the C.I. that include intelligent behavior observed in groups of non-human agents (e.g. ant colonies, robotic swarms, etc.): "Collective intelligence is the totality of processes that lead to the emergence of either new knowledge, intelligent decisions, or behavior, within a group of agents coupled by sharing a common memory, or any other means to record and process information about the activity of the group".

According to this definition, a key element of any system capable of collective intelligence is the "aggregator" (see also Ickler, 2010), an instance that collects and fuses the raw data derived from the activity of the agents, and – in some cases – makes the result available to the agents as a shared memory (see figure 1). Thus, the aggregator is the "secret" ingredient that makes the difference between a collection of agents, and a system capable of intelligent behavior as a whole.

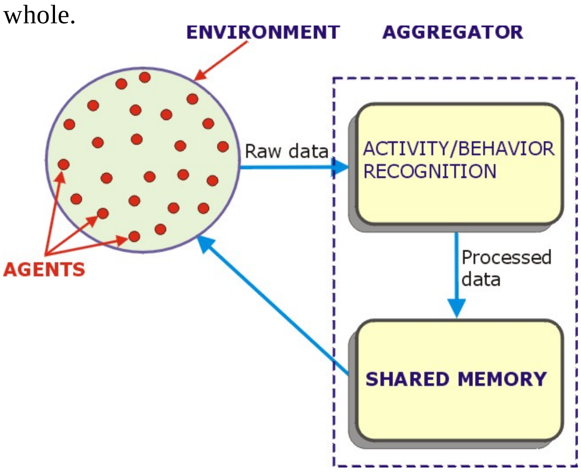

Fig.1. The general structure of a C.I. system, illustrating the role of the aggregator.

Note that, in the case of the systems composed of very simple agents (e.g. ant colonies) the role of the aggregator is played by the environment shared by the agents.

Starting from the model presented in figure 1, we performed a review of the literature, with the aim to identify the main approaches used in the study/implementation of systems capable of C.I. This paper is a brief report presenting the conclusions of this review.

The following section is dedicated to the presentation of the means for (automatic) sensing the activity of the agents , while Section 3 deals with the problem of modeling C.I. systems. Finally, Section 4 is reserved for conclusions.

2. SENSING THE ACTIVITY OF THE AGENTS IN C.I. SYSTEMS

It should be said from the beginning, that the majority of the research literature regarding C.I. assumes systems with human agents. Therefore, for this report we will also accept this assumption.

Basically, most of the works on the topics related to C.I. attempt to provide answers to the following questions:

a. "How can people and computers be connected so that—collectively—they act more intelligently than any person, group, or computer has ever done before" (The M.I.T Center for Collective Intelligence - http://cci.mit.edu/).

b. "Is the way in which individuals interact, intentionally or unintentionally, designed to maximize global benefit?" (Olguin et al. 2011). And, as a corollary to this question, are there any means *to influence the interactions* between the agents in order to optimize the global benefit?

A simple taxonomy of the C.I. systems based on the type of interaction between the agents (proposed in Susnea, 2016) is shown in figure 2.

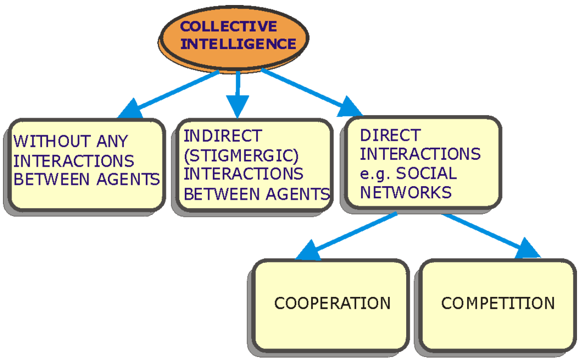

Fig.2. A simple taxonomy of systems with C.I. based on the type of interactions between the agents.

Of course, there are other proposed taxonomies for C.I. For instance, Olguin et al. (2011) use the granularity of the perspective to make a distinction between the individual, group, social network, organization, community, and whole society levels. Salminen (2012) sorts the literature starting from the level of abstraction, and distinguishes a micro level (e.g. the factors that define humans as social animals: social and emotional intelligence, motivation to participate in communities, etc.), a macro level (e.g. decision making, wisdom of crowds), and the emergence (e.g. stigmergy, self-organization).
From an engineering perspective, we are less concerned about the theoretical considerations,

and more interested in practical solutions for the implementation of systems having the general structure depicted in figure 1.

Following this perspective, the fundamental question for the implementation of a technological system addressing the C.I. seems to be: "what are the behavioral cues relevant for C.I. and what are the technical means to capture them? ".

The simplest way to capture such behavioral cues is to design special wearable sensors. See Olguin (2009a; 2009b) for the detailed description of a so-called "sociometric badge" capable to detect and record/transmit information about:

- physical activity of the user (by means of a 3-axis accelerometer)
- speech activity (using a microphone and additional signal processing circuits)
- face to face interactions (using an infrared receiver/transmitter)
- proximity (through the use of a RSSI device, i.e. a Radio Signal Strength Indicator).

Despite the obvious advantages, the solutions based on wearable sensors have limited applicability, due to the some physical discomfort, and the similarities with the electronic devices for personal tagging used by the correctional systems in the USA and UK..

Therefore, in practice the preferred solutions rely on sensors deployed in the environment most often for audio and visual observations. There are however simpler solutions based on the use of passive infrared (PIR) motion detectors (see Vasiliu, 2016), or RFID (Susnea & Vasiliu, 2011).

In another interesting approach, simply being in a certain place (e.g. near a specific shelf in a supermarket, or in a certain room, or passing through a certain door, etc.) contains indirect information about the activity of the agents, and it is possible to design applications based on integrating this type of information across a group of agents (see: Susnea, 2012; Susnea, 2015; Susnea & Axenie, 2015).

In a comprehensive review, Daniel Gatica-Perez (2009) focuses on the nonverbal communication between members of small groups. After reviewing about 100 articles on these topics, Gatica-Perez identifies 4 main research directions in what concerns the automatic decoding of nonverbal communication cues:

- Automatic identification of the interacting agents ("who is talking and when" – turn-taking, and "who is talking to whom" – addressing). This problem is mainly solved through the analysis of the head pose, as an indicator of the gaze and visual focus of attention. Notable works on this topic are (Ba & Odobez, 2006, and Stiefelhagen et al., 2002).

- Modeling the internal states (such as interest, attention, boredom, anger etc.) of the participating agents. An interesting way to detect such internal states is by recognizing laughters bursts in audio streams (see Neiberg et al, 2006 and Kennedy & Ellis, 2004).

- Automatic identification of some personality traits such as dominance or extraversion (Kulyk et al, 2005; Rienks & Heylen, 2005).

- Automatic identification of the relationships (e.g. social roles) between the agents (Favre et al, 2008; Zancanaro et al, 2006).

In an attempt to generalize the wide variety of applications based on the automatic recognition of human activity, Vinciarelli et al (2009) introduce the concept of "social signal processing" and describes the following possible sources of raw data:

- Physical Appearance
- Gesture and Posture
- Gaze and Face
- Vocal Behaviour
- Position in Space and Environment

Social network analysis is another (vast) research direction is the study of collective intelligence. To get an idea of the interest on this topic, note that the book (Scott, 2012) accumulated over 11,000 citations since 2012, and an article describing a specific software application for social network analysis (Borgatti et al, 2002) also counts over 6,000 citations.

To conclude this brief review of the solutions for sensing the activity of human agents, we will cite with the opinion of Gatica-Perez (2009), who states: *"Despite the large progress in social psychology and cognition, no single theory can answer the questions of what specific cues and what concrete integration mechanisms are used to make sense of each social situation. Furthermore, such theories might not exist at all."*

3. MODELING THE COLLECTIVE INTELLIGENCE

Collective Intelligence is a notoriously elusive and hard to model concept (see Susnea, 2016). Therefore, the preferred solution for practical problems related to C.I. remains the Agent-Based Modeling, ABM (see Scarlat & Maries, 2010). According to Bonabeau (2002), "ABM is a mindset more than a technology. The ABM mindset consists of describing a system from the perspective of its constituent units."

Basically, an ABM system is a set of relatively simple autonomous agents, operating in a well defined environment, according to a set of behavioural rules. The agents have limited perception capabilities, and they usually interact only with similar agents located in their immediate neighborhood. Most often, these agents are not even aware of the global behavior of the system.
A variety of computational resources for ABM have been developed in the past decades. A comprehensive list is available at the web address: https://www.openabm.org/modeling-platforms.
The most popular platforms seems to be: NetLogo (Wilensky, 1999), REPAST (Collier, 2003), and MASON (http://cs.gmu.edu/-eclab/projects/mason/). Among these tools, NetLogo is probably the best documented platform, and has the largest library of open source models.

3.1. An example of ABM simulation

We have edited one of the NetLogo library models – the cooperation model (Wilensky, 1997) in an attempt to answer a "classic" question: "Why is Romania different? What is the reason for Romanian people as a nation always perform below their potential, while most Romanian individual emigrants have a good social evolution in the new country where they settle" (see Boia, 2012).
To this purpose, we created an ABM model with two input variables: the percentage of agents who abide a certain system rule, and the availability of a general "resource" (food/energy), and two output variables, namely the final number of rule abiding agents, and the number of rule breakers.

The simulation results are presented in figures 3, and 4. As expected, rule breaking is "contagious". If the initial number of rule breakers is higher than a certain value (around 10% of the initial population), the system evolves toward a state where everybody breaks the rules (see fig. 3).

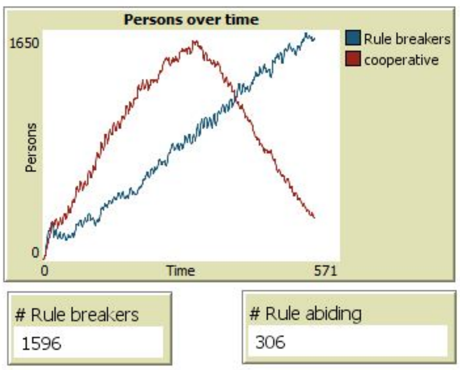

Fig.3. Rule breaking appears to be contagious

On the contrary, when the initial number of rule breakers is low, the cooperative agents clearly dominate (fig. 4).

One interesting detail revealed by the simulation is that the scarcity of the shared resource aggravates the process of rule decay. Poverty seems to undermine the social rules, even when the initial number of rule breakers is low (see fig. 5)
We also noticed that the spatial distribution of agents cooperative agents versus rule breaking agents tends to show an obvious clusterization. Rule breakers settle in compact neighborhoods that tend to expand spatially, as the poverty aggravates (see fig. 6).

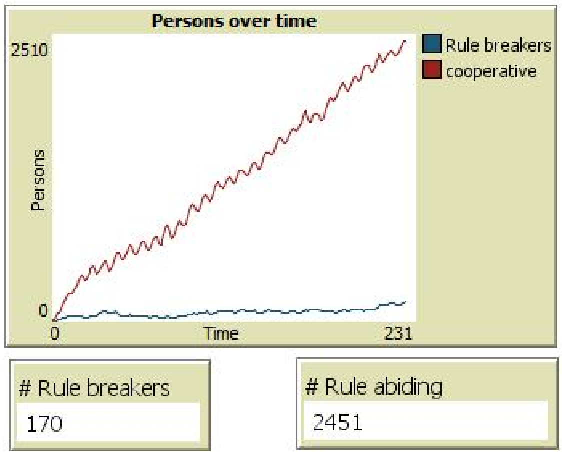

Fig.4. When the initial number of rule breakers is low, the cooperative agents clearly dominate

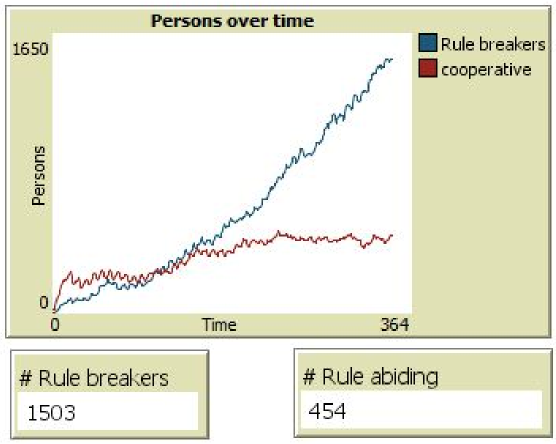

Fig.5. Poverty seems to undermine the social rules, even when the initial number of rule breakers is low

It seems that widely accepted social rules are an excellent aggregator for collective intelligence, by channeling the energies of the agents towards a common goal. From this perspective, a large number of traffic offenders, for instance, might be a an indicator of delays in the overall progress of a society.

To conclude, the ABM answer to the question formulated by Lucian Boia (“Why is Romania different?” - Boia, 2012) is: “Poverty combined with the wide-spread habit of disregarding the rules”.

Fig.6. The spatial clusterization effect

3.2. Other applications of ABM

Singh & Gupta (2009) and Bonabeau (2002) enumerate several popular applications of ABM. Here are several examples:

- Vehicular traffic (Gerhenson, 2004),
- Passenger flow & smart evacuation systems (Almeida, 2012; Stamatopoulou et al, 2012),
- Health care (El-Sayed et al, 2012),
- Urban planning (Batty, 2007),
- Logistics (Gjerdum et al, 2001),
- Economy and market research (Tesfatsion, & Judd, 2006).

4. CONCLUSIONS

This paper continues the effort of a systematic review of the vast literature related to C.I. started in (Susnea, 2016) with the aim to clarify the terminology and identify the main research directions in the design of C.I. systems. Also, a simple ABM simulation showed that social rules are a good C.I. aggregator.

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