Improving QoE in Multi-layer Social Sensing: A Cognitive Architecture and Game Theoretic Model

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ABSTRACT

This paper proposes a novel cognitive architecture and game-theoretic model for resource sharing among netizens, thus improving their quality of experience (QoE), in multi-layer social sensing environments. The underlying approach is to quantify micro-rewards and inequalities derived from social multi-layer interactions. Specifically, we model our society as a social multi-layer network of individuals or groups of individuals (nodes), where the layers represent multiple channels of interactions (on various services). The weighted edges correspond to the multiple social relationships between nodes participating in different services, reflecting the importance assigned to each of these edges and are defined based on the concepts of awareness and homophily. Heterogeneity, both interactions-wise on the multiple layers and related to homophily between individuals, on each node and layer of a weighted multiplex network produces a complex multi-scale interplay between nodes in the multi-layer structure. Applying game theory, we quantify the impact of heterogeneity on the evolutionary dynamics of social sensing through a data driven approach based on the propagation of individual-level micro-affirmations and micro-inequalities. The micro-packets of energy continuously exchanged between nodes may impact positively or negatively on their social behaviors, producing peaks of extreme dissatisfaction and in some cases a form of distress. Quantifying the evolutionary dynamics of human behaviors enables the detection of such peaks in the population and enable us design a targeted control mechanism, where social rewards and self-healing help improve the QoE of netizens.

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Keywords

Cognitive architecture; game theory; multi-layer networks; social sensing; QoE; IoP

1. INTRODUCTION

Recent years have witnessed an unprecedented diffusion of smart devices (e.g., smartphones), mobile and pervasive technologies supporting a wide variety of applications in our daily lives. Indeed, in the era of *cyber-physical-human* convergence [5], there exist intricate interplay and interactions among the physical world, the cyber world, and the human world, leading to an interesting paradigm called the *Internet of People* (IoP), as envisioned in [6]. In the cyber-physical systems (CPS), sensors and smart devices pervasively embedded in the environment collect data about physical phenomena of interest, which are then analyzed in the cyber world to extract meaningful patterns and knowledge, followed by intelligent decision making and actionable control inferences that are fed back to the physical world for improved performance. Additionally, humans carrying smartphones and mobile devices can also act as participatory or "social sensors" to not only collect data, but also interact with the physical and cyber worlds to effect changes. Thus, human behavior and social dynamics play significant roles in understanding complex behavior of our cyber-physical-human world, putting people at the centre of this novel IoP paradigm. Participatory sensing (also called crowdsensing), is based on explicit and voluntary participation of human beings in the sensing process about environmental phenomena [2]. In this paradigm, individuals become contributors and the importance of their contributions may benefit the whole social community. Here both the "quantity" (i.e., degree of participation) and the "quality" of information (i.e., accuracy or truthfulness of contribution) [11, 2] are crucial.

In social sensing, while exchanging information, individuals or groups of netizens are typically eager to receive rewards and signs of appreciation from people they interact with; they also become distressed if there are signs of disrespect and unfriendliness. Peaks of extreme dissatisfaction at the individual or group level may generate profound distress (e.g., loss of motivation), violent behavior (e.g., suicide) [13], and other symptoms (e.g., action class, boycott). We envision that a cognitive architecture [8] based on social sensing coupled with the concept of Internet of People (IoP) is capable of sensing and spreading such contagion and subsequently healing and re-balancing with some rewards in terms of net opportunities. Furthermore, in the physical and cyber worlds, netizens interact with each other through multiple channels, corresponding to different smart spaces. Hence it is fundamental to define a complex socio-technical system involving social, economic and cognitive facets from the IoP perspective [6].

Recognizing that the cognitive aspect must incorporate human behaviors that play important role in efficient system operations, and in order to capture the effect of multiple types of social interactions, in this paper we propose a model based on the concept of social multiplex or *multi-layer network* of netizens [7, 3]. In this model, the behavior of individuals (nodes) and the importance (weight) that a node assigns to the links, are derived from multiple factors influencing the overall behavioral dynamics of the multiplex network. One key factor is called *homophily*, the principle that similarity breeds connection [7, 14, 9]. It shapes human interactions and the emergence of cooperation between individuals, influencing both the formation of cooperative groups in different parts (layers) of the network and the group size [7]. Another driving factor impacting the spreading in a social contagion process is *awareness*, which changes human susceptibility and individual approach towards contagion [15, 13].

Now, behaviors and relationships among individuals or groups trigger psychological and unconscious biases produced by human brain, which may be positive (e.g., satisfaction) or negative feelings (e.g., distress), thus impacting on their behaviors and choices. To this end, we incorporate such biases in our proposed cognitive architecture (see Fig. 2) by including two key concepts, namely *micro-inequalities* (or micro-inequities) and *micro-affirmations*, that act in opposite directions and represent two manifestations of biases [12]. Finally, to analyze the evolutionary dynamics of behaviors in social multi-layer networks, we apply evolutionary game theory [7, 14], assuming each interaction generates micro-reward or micro-dissatisfaction depending on the game-theoretic strategies.

The communities or groups to which individuals belong, are defined by weighted links, where the weights depend on the awareness and homophily. Communities together with psychological biases, quantified by micro-affirmations, micro-inequities, homophily and awareness, shape their behaviors on the social multiplex network and drive the selection of strategies over various rounds of the game. Quantifying the evolutionary dynamics of behaviors enables detection of peaks of extreme dissatisfaction in the population. Our aim is to model and quantify the propagation of micro-packets of positive and negative energy, and realize a social rewarding mechanism based on this evolutionary dynamics. To this aim, we introduce a control mechanism, where social rewards and self-healing of netizens' peaks of dissatisfaction help improve their *quality of experience* (QoE).

The remainder of the paper is organized as follows. Section 2 defines multi-layer networks representing multi-layer social sensing. Section 3 proposes the cognitive architecture, focusing on the role of awareness. Section 4 presents the game theoretic model describing the evolutionary dynamics of social behaviors and the control mechanism. Section 5 discusses a possible application scenario of our novel approach. Section 6 concludes the paper with directions of future research.

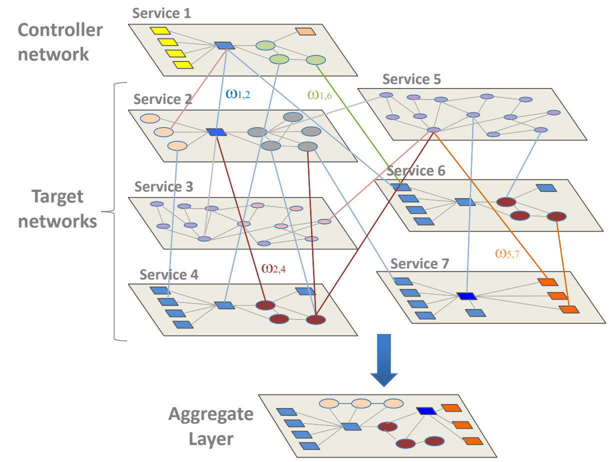

Figure 1: Multi-layer social sensing and control mechanism. In real-world complex networks, individuals interact via multiple layers (e.g. $M = 7$ in this figure) corresponding to different services. Colors identify groups of nodes and lines represent multiple interactions within layers (intra-layer) and between nodes belonging to different layers (inter-layer). The figure also describes the control mechanism in multi-layer social sensing.

2. MULTI-LAYER SOCIAL SENSING

Relationships between individuals are typically multi - relational in nature. Multi-layer networks [7, 3] allow us to encompass multiple interactions and relationships, exploring and unveiling how different ties in various layers can impact on the diffusion of social behaviours. An interaction in a given layer may trigger specific behaviors in another layer or alter netizens' attitude towards some individuals or groups, due to simultaneous inter-layer interactions on a different channel (or link). Such multiple types of interactions correspond to the layers of a social multiplex network, where the nodes represent individuals or groups, and their connections (links) on the different layers are based on the nature of interactions [7, 15, 13]. Social multiplex networks thus enable us to evaluate the impact of various interactions among individuals or groups, including social environments (e.g. workplace, friends circle, etc.), which may influence their overall habits, choices and behaviors in daily life. In the context of a smart city, for example, the layers may represent various services and types of data for different services used by the netizens (see Fig. 1). The multiplex structure also incorporates the concept of heterogeneity [13, 15], representing interactions in multiple layers as well as individuals' profiles, which produces a complex interplay in multiple scales (both spatial and temporal). Human reactions and behaviors are the result of multi-scale social interactions in such social multi-layer networks [3].

3. COGNITIVE ARCHITECTURE

In this work, we propose a cognitive architecture leveraging data sensed by the people (contributors) and aiming to improve the QoE of netizens. Fig. 2 describes the steps of the cognitive (middleware) architecture based on a multi-level sensing; it primarily depends on the quantity and quality (QnQ) [2] of the sensed data. Step 1 of the architecture consists of an initialization of the network with the classification of citizens in various classes [2]. One of the main challenges in crowdsensing applications is attributed to false contributions due to selfish and malicious actions, or wrong perception of an event [2]. These false contributions may affect the operation of the underlying systems or applications. Thus it is vital to devise a reputation model, similar to the QnQ model, to distinguish individuals in different classes. Detection of selfish, malicious and honest ciizens depends on the quality of contribution (i.e., accuracy) and quantity (i.e., degree of participation) [2]. The reputation scores help make reputation-aware decisions and hence improve the operational reliability of the application services. The proposed cognitive middleware classifies the network nodes according to their contributions, thus allowing us to characterize individuals or groups based on their interactions and measured levels of homophily and awareness (weights). For this purpose, we construct a weighted social multiplex network of citizens (Step 1 in Fig. 2). The weights in the multi-layer structure correspond to the measures of awareness and homophily as defined in [13]. The multiple layers represent different types of interactions between citizens corresponding to the services they contribute to, implying the multi-layer topology of connections may also change.

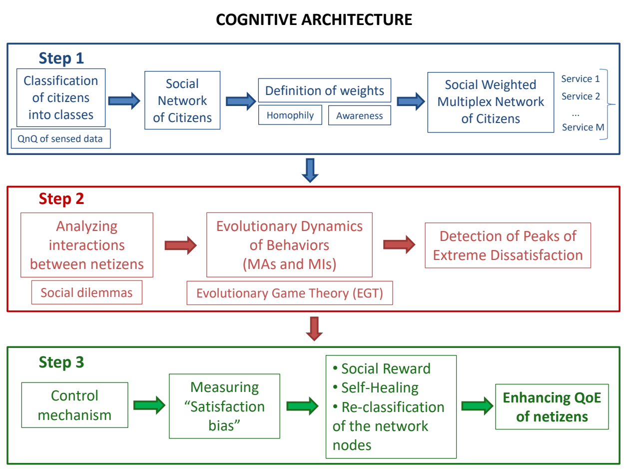

Figure 2: Cognitive (Middleware) Architecture.

Step 2 of the proposed architecture is based on the game theoretic model that analyzes and quantifies the evolutionary dynamics of behaviors on the social multiplex network of netizens. To explore emergent behaviors, we consider evolutionary game theory (EGT) on the previously defined social multi-layer networks [7, 14]. Additionally, we define a pairwise social dilemma, the Snowdrift Game (SG), to be played by the nodes in the multiplex structure. Payoffs derived from the rule set of the game, played by individuals in the social multi-layer network, allow us to quantify the emergence of strategies and the accumulation of biases - micro-affirmations (MAs) and micro-inequities (MIs) at each round of the game. Thus, we measure the level of dissatisfaction and detect the peaks of extreme dissatisfaction.

Since the peaks may generate a form of distress, Step 3 of the cognitive architecture proposes a control mechanism. The satisfaction bias and the measures related to the observed behaviors and psychological biases, feed a social reward mechanism as well as a self-healing mechanism provided by the network itself and help improve the QoE of netizens. Thus, the control mechanism is a feedback loop, which is the result of various steps of the cognitive architecture, encompassing the complex interplay of evolutionary dynamics on the multi-layer social structure.

3.1 The Role of Awareness in Distress Propagation

Multiplexity of netizens triggers propagation of awareness about a phenomenon through interactions in both social and real (human) networks. The heterogeneity of humans, on one hand, leads to "think and react" differently to social phenomena; on the other hand, the similarity among individuals drive people to weigh interactions influencing a probable contagion effect and the subsequent spreading dynamics. A phenomenon of spreading, such as a social contagion, depends on the nature of ties [4], encompassing quality and quantity of events as opportunities of interactions. A large body of literature has demonstrated how the social contagion is referred to something that spreads inter-personally [4] such as behaviors, rumors, information, infectious diseases and emotions. To quantify the impact of heterogeneity of nodes and the role of homophily (i.e., the tendency to associate and interact more with similar people) [15, 7, 14] on the spreading dynamics, we need to explore the co-evolution of two diffusion processes, namely social contagion and awareness, in the same weighted multiplex network, where the weights depend on both awareness and homophily. The interplay between these two processes leads to unveil how the awareness can play a pivotal role into the spreading [13, 15]. The more netizens are aware of the spreading, the more they are able to adopt strategies to improve the ability of self-protecting [15]. Modeling our society into a social multiplex structure constitutes the most suitable infrastructure for analyzing such dynamical processes and their complex evolution. For this reason, in [13], the co-evolution of these processes has been explored in different layers of the same weighted multiplex network, with the aim of studying the joint resulting effect in a realistic scenario. The weights of ties between the nodes reflect their intensity in terms of quality and quantity of interactions. It has been demonstrated that people's health is linked to our behaviour and consequently with the social ties and environment [13].

The connectivity in the social network has also an impact on distress and depression, happiness and loneliness [4]. Many studies have argued that distress and depression may shape the network of individuals and their connectivity. Therefore, we consider the energy of micro-affirmations and micro-inequities that change the opportunity to have interactions with some individuals, due often to distress and unfair treatment. In turn, this can affect people's well-being in several ways, reaching peaks of dissatisfaction for individuals or groups. The connectedness of people in a social context can also lead to lower self-esteem and dissatisfaction.

4. A GAME-THEORETIC MODEL

Individuals and groups continuously communicate via the underlying multiplex network and each of these interactions may generate a micro-reward or alternatively a negative feeling of disrespect or unfriendliness (micro-dissatisfaction).

As in [12], these aspects represent psychological biases often deriving from quick judgments of people and situations, and depend on our individual experiences or the environment we live in. Such biases occur automatically or implicitly, and may impact the individual's overall level of dissatisfaction, thus modifying our social behaviors. More precisely, *micro-inequalities* or *micro-inequities* (MIs) are defined as "apparently small events that are often ephemeral and hard-to-prove events which are covert, often unintentional, and frequently unrecognized by the perpetrator. This occurs wherever people are perceived to be different" [12], and corresponds to one of the manifestations of unconscious bias. To counterbalance such negative biases, the concept of *micro-affirmations* (MA) is defined as [12] "apparently small acts, which are often ephemeral and hard-to-see events that are public and private, often unconscious but very effective, which occur wherever people wish to help others to succeed." In fact, if individuals are constantly proactive about rewarding and professing the achievements of others, people will be less inclined to micro-inequities and a reciprocity effect will be triggered, producing a psychological reward. It is important to observe how the concept of micro-inequities is strictly linked to "distress". In particular, an individual in mental distress could exhibit some symptoms, such as anxiety or depression that may be caused by dissatisfaction. Dissatisfaction, as a sum of negative experiences (i.e, MIs), could therefore influence the level of distress and its evolution, thereby influencing the onset of a future mental ill-health [13]. By introducing and quantifying the propagation and the evolution of behaviors derived from a sum of micro-inequities or micro-affirmations, we can quantify the dissatisfaction level of an individual with possible impact on the distress. Furthermore, by translating unconscious biases in game-theoretic terms, we can quantify the balance of MIs and MAs by defining a factor ψ_i, which is linked to environmental factors (e.g., cultural, geographical, social, etc.) and emotional states, influencing our choices and behaviors. Here, ψ_i is defined as follows:

$$\psi_i = 1 - (\psi_{i_{max}} - \psi_{i_{min}}) \left[1 - \sum_j \frac{MI_{ji}}{MA_{ji} + MI_{ji}} \right] \quad (1)$$

where MA_{ji} and MI_{ji} are respectively the MA and MI values obtained at each round of the game by node i from its interactions with the neighboring nodes j. At each round, the factor ψ_i is calculated in game-theoretic terms by considering the payoffs obtained by node i in the previous round of the game. In particular, if a node gets a "positive" payoff, then it will get an MA value, otherwise an MI value. Thus, ψ_i generates a bias in netizens' behaviors as follows. If $MI_{ji} \geq MA_{ji}$, a player will have a higher tendency to change its strategy in the next round of the game. This is mainly due to a sort of 'dissatisfaction' of the individual after previous interactions with others in the multi-layer network. Otherwise, if $MI_{ji} \leq MA_{ji}$, it means node i has experienced micro-rewards from its interactions ("positive" payoff), hence it will likely tend to keep the same choice adopted in the previous round. Note that ψ_i acts as a key bias towards a change in strategy when $MI_{ji} \gg MA_{ji}$, which means a strong imbalance of MI over MA. On the other hand, if $MA_{ji} \gg MI_{ji}$, a node tends to keep the same strategy of the previous round. The two limit values, $\psi_{i_{max}} = 1$ and $\psi_{i_{min}} = 0.1$, are chosen to avoid "frozen states".

4.1 Evolutionary Dynamics of Behaviors

In order to investigate and quantify the evolutionary dynamics of behaviors in the multiplex networks, we adopt the Snowdrift Game (SG), a pairwise social dilemma where the nodes can select one of two strategies - cooperation or defection. SG is a symmetric game and suitable for describing realistic scenarios where a task has to be done [14], e.g., an application based on crowdsensing. Each player can decide to put an effort to cooperate (i.e., contributing and participating to the task) such that he decides to pay a cost of providing the contribution. To accomplish the task, it is crucial to have a robust quality of information (QoI) in the sense that the task will be done efficiently only if the other player also contributes. However, there could be users who decide to defect, such as not paying any cost of contribution for accomplishing the task, or relying on the contributions of others. In this case, if the other player decides to defect, the task will not be accomplished with a negative effect for both players. Overall, although this type of game represents a "coexistence game", since most often both strategies end up coexisting, direct and indirect reciprocity as well as other mechanisms [10] may change the fitness of the strategies over time, leading to the evolution of cooperation termed as Evolutionarily Stable Strategy (ESS). In particular, we assume the iterated form of SG, i.e., Iterated Snowdrift Game (ISG), where in each round of the game, the nodes play with each other and accumulate payoffs obtained from each interaction over all the rounds of the game. After each round, the players have the opportunity to change their strategies or behavior, based on an imitation dynamics of the fittest strategies [7, 14].

4.2 Control Mechanism

Step 3 of the proposed cognitive architecture (see Fig. 2) introduces a control mechanism of reward. Thus, we evaluate the evolutionary dynamics in a relatively long time-span (temporal) window involving a certain number of rounds of the game, and measure some statistical estimators related to the netizens' behaviors. Starting from a measure of cooperativeness, i.e., the "social honesty" of citizens, we measure the level of satisfaction, namely the "satisfaction bias", obtained by each node through the evolutionary dynamics of the social multiplex network (see Step 2 in Fig. 2). If the social honesty of individuals is relatively high, the social multiplex network will reward them with social macro-reward. This represents self-healing of the network, avoiding these nodes to reach peaks of dissatisfaction in near future. Satisfaction bias also acts as a modulator of future strategies of the network nodes, in fact if this value is relatively high, then individuals are inclined to keep cooperating and participate in multi-level sensing. On the other hand, if the bias has an extremely negative value, it means that the node is experiencing a high level of dissatisfaction and consequently the self-healing mechanism becomes crucial to counterbalance the dissatisfaction level. Self-healing is therefore based on this control mechanism and aims at improving the QoE of the netizens. Moreover, Step 3 of the cognitive architecture allows re-classifying the network nodes in the different classes of behaviors, based on the quality and quantity of the sensed data [2]. The control mechanism is conceptually illustrated in Fig. 1 consisting of two kinds of networks, namely the controller network and the target network. This requires that the time scale separation of activities in the controller network is smaller than those in the target network. The role of the controller results from the coupling between various layers. It may change dynamically over time based on the network inter-layer strength $\omega_{\alpha\beta}$, which indicates the degree of inter-layer coupling between two generic layers α and β. The schematic illustration in Fig. 1 considers $M = 7$ layers, where one of them acts as the controller network while the others as target networks. Those layers having a higher inter-layer strength behave as dominant layers of the multi-layer structure, with a stronger impact on the dynamics [7]. The aggregate layer (or network) contains multi-layer structural information coming from different types of data related to multiple services towards integrated policies and a final decision.

To measure and quantify the social honesty of each individual, we define the statistical estimator γ_i as follows:

$$\gamma_i = \sum_i (NC)_{i|t-1}/N_r, \tag{2}$$

where NC is the number of cooperative behaviors in the previous $t-1$ rounds of the game before feedback, while N_r is the number of rounds before feedback, occurring at time step t. Here γ_i ranges in $[0,1]$ such that $\gamma_i = 0$ reflects a lack of cooperativeness, while $\gamma_i = 1$ means that a node has been fully cooperative with a proactive attitude towards its social community. γ_i quantifies the degree of cooperativeness of each individual in the network, and at each temporal window, it allows us to re-classify the contributors in one of the three classes: selfish or malicious actions, or wrong perception of the event [2]. Moreover, γ_i can produce a remarkable MA or MI values as a reaction to his behavior. Such network bias is quantified through another statistical estimator ϵ_i, called "satisfaction bias", defined as the ratio between the number of MAs or MIs obtained in all the rounds before the control mechanism and the total number of rounds in the same temporal window. Depending on the sign of the bias, a dual definition of ϵ_i in case of a positive bias, is given as follows:

$$\epsilon_i = \sum_i MA_{i|t-1}/N_r, \tag{3}$$

whereas in the case of a negative bias, it is defined as:

$$\epsilon_i = \sum_i MI_{i|t-1}/N_r. \tag{4}$$

The "satisfaction bias" amplifies the number of MAs or MIs, impacting on ψ_i and, in turn, on the strategy adoption process. Specifically, we can define a threshold γ_{th} such that $\gamma_i \geq \gamma_{th}$ implies the individual (node) experienced a positive feedback from the community, resulting in $MA = MA + \epsilon_i \cdot MA$; whereas if $\gamma_i < \gamma_{th}$, the node experienced a negative feedback resulting in $MI = MI + \epsilon_i \cdot MI$. Thus, the satisfaction bias modulates the netizens' behaviors in subsequent rounds of the game, pushing them to actively participate in multi-level sensing or defecting due to the high level of dissatisfaction.

5. PUTTING IT TOGETHER: AN APPLICATION SCENARIO

The proposed cognitive architecture and game-theoretic model open up intertwined directions on modeling and machine learning, since it proposes an innovative multi-scale learning method based on multi-layer social sensing. Netizens, along with their human traits and psychological biases, assume a central role in the delivery of services in crowdsensing application scenarios. Only by analyzing social behaviors and their unconscious biases, we are able to design targeted people-centric services. We therefore propose a multi-scale integration learning method based on our cognitive architecture that is able to merge different aspects. For example, we can analyze macro-, meso- and micro-scale network properties related to the nodes (netizens) and the layers (services), and a conceptualization of social sensing based on complex networks. Similarly, our game-theoretic modeling approach aims at analyzing the evolutionary dynamics of social interactions on the multi-layer network, including the quantification of unconscious biases. Finally, the control mechanism, which consists of self-healing and social rewarding, flows from the requirements provided by the network itself and its constituents or actors as discussed aspects. To sum up, the multi-layer social sensing cognitive architecture and the game-theoretic model suggest a novel complex learning approach and guidelines to improve the netizens' QoE [13]. The game-theoretic model also enables us to dynamically explore changes in the network architecture with applicability in a variety of crowdsensing scenarios, such as vehicular traffic monitoring and management [2, 1].

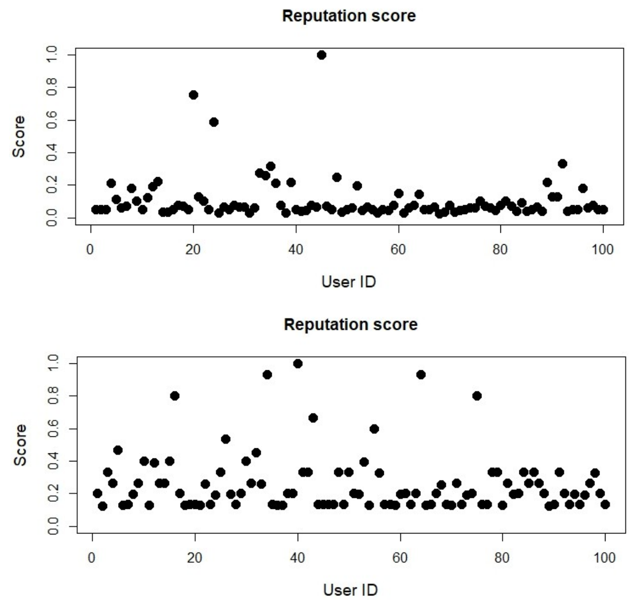

Figure 3: Reputation score of each user (a) before applying control mechanism, and (b) after applying control mechanism.

We have simulated a simple scenario of crowdsensing applications (services) using synthetic data generated following an approach similar to that in [2]. As discussed earlier, we consider the quantity and quality of the reported events. They represent the contributors' profiles and have been used as input data. Then, following the proposed cognitive architecture and game-theoretic model, we have measured the reputation score for each node before and after the control mechanisms. The reputation score for each individual is calculated as a function of the quality and quantity of data provided by the individual [2], and the contributors' profiles are updated by applying the proposed control mechanism. Fig. 3 shows that the overall reputation score for each individual (represented as a node in our multi-layer social sensing network) increases due to the self-healing mechanism. The linkage between the measured reputation score is made through the social honesty (γ_i) of individuals, that changes at each control mechanism. This mechanism acts on the netizens' behaviors and strategy updates through the social honesty and satisfaction bias (ϵ_i). These two statistical estimators act on MAs and MIs and then on the factor ψ_i, thereby modulating the behaviors in strategy update at each control. A high reputation score after applying the control mechanism means that the attitude of the netizens becomes increasingly cooperative. And, an overall increase in the reputation score implies that the average "happiness", and hence the quality of experience (QoE), is increasing even more for those citizens who experience a higher level of dissatisfaction. Thus, the control mechanism is able to partially counterbalance their dissatisfaction levels. More detailed experiments and validation of various steps of our proposed cognitive architecture and the concepts presented in the game-theoretic model are ongoing.

6. CONCLUSIONS

Connectedness among people in multiple spaces of interactions, knowledge, awareness and homophily, in addition to unconscious psychological biases, represent the basic building blocks of the novel cognitive architecture for multi-layer social sensing proposed in this paper. Since enormous volume of data for groups of individuals can be collected, stored and analyzed, the proposed architecture essentially aims at leveraging the sensed data to build an Internet of People (IoP) framework. Thus the IoP-based cognitive architecture aiming to sense the nodes (individuals) and groups (clusters) with a common unfair treatment, provides a novel definition of the weight of social interactions, including the concepts of awareness and homophily. While the individuals continuously interact in the social multiplex network exchanging micro-packets of energy, i.e., micro-affirmations and micro-inequities, we investigate the evolutionary dynamics of the netizens' behaviors. This allows us to detect the peaks of extreme dissatisfaction and study the impact of heterogeneity and homophily in the diffusion of distress into the network among the netizens.

The cognitive architecture provides a control mechanism, based on the co-evolution of complex behaviors and sensed data, and assigns a social reward based on the evolutionary dynamics. Micro-affirmations and micro-inequalities are quantum packets of information exchanged between the individuals, and constitute the best units of information handled by the game-theoretic model.

We envisage that the game-theoretic approach will be extremely useful in validating the efficacy of the complex cognitive architecture based on a multi-layer social sensing, in particular crowdsensing application scenarios, with the help of real data sets. Moreover, in order to investigate the dynamic impact of weight on the evolutionary dynamics in the multi-layer social sensing, it could be extremely interesting to consider an evolving measure of weight which is function of player's MAs or MIs, thus individuals are pushed to strengthen links with those nodes with whom they have experienced positive and rewarding interactions. Our approach has far-reaching implications and is expected to result in modeling cognitive architectures that are trustworthy and also understanding human behavior dynamics that are more predictable.

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