A Novel Methodology for designing Policies in Mobile Crowdsensing Systems

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Abstract

Mobile crowdsensing is a people-centric sensing system based on users’ contributions and incentive mechanisms aim at stimulating them. In our work, we have rethought the design of incentive mechanisms through a game-theoretic methodology. Thus, we have introduced a multi-layer social sensing framework, where humans as social sensors interact on multiple social layers and various services. We have proposed to weigh these dynamic interactions by including the concept of homophily, that is a human-related factor related to the similarity and frequency of interactions on the multiplex network. We have modeled the evolutionary dynamics of sensing behaviours by defining a mathematical framework based on multiplex EGT, quantifying the impact of homophily, network heterogeneity and various social dilemmas. We have detected the configurations of social dilemmas and network structures that lead to the emergence and sustainability of human cooperation. Moreover, we have defined and evaluated local and global Nash equilibrium points by including the concepts of homophily and heterogeneity. Therefore, we have analytically defined and measured novel statistical measures of QoI and user reputation scores based on the evolutionary dynamics. Measures are distinct for the different configurations and higher for the most cooperative ones. Through the proposed methodology we have defined the core of a DSS for designing novel incentive mechanisms by operating on the policies in terms of QoI and user reputation scores.

Keywords: Mobile crowdsensing, Multi-layer Social sensing, Game theory, Homophily, Reputation score, Decision Support System

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1. Introduction

Recently, we have been witnessing with a widespread diffusion and adoption of mobile devices, such as smartphones and tablets, becoming essential in our daily lives \cite{1, 2, 3, 4}. In addition, the integration of more and more embedded sensors (GPS, gyroscope, camera, etc.) into these devices, along with improved processing power and storage capacities, have enhanced their sensing capabilities \cite{2, 4}. In parallel, the growth of mobile networks and wireless communication technologies have resulted in a better connectivity among users’ devices and vehicular systems \cite{4}. Overall, these enhanced mobile and pervasive technologies have led to an increasing development of a wide range of applications \cite{1, 4} that are part of the paradigm termed as Mobile Crowdsensing (MCS). MCS is therefore a people-centric sensing system based on human voluntary participation or contribution about some phenomena in their surrounding environment, namely human users with their personal mobile devices acquire local information (e.g. geo-spatial) and share their knowledge or measures with other users and communities in the network \cite{3, 1, 5}. Thus, this large-scale sensing paradigm leverages the collaborative approach of individuals contributing to measure phenomena of mutual interest \cite{1, 3, 6}. MCS is a clear example of the cyber-physical convergence phenomenon, leading to the Internet of People (IoP) paradigm, as conceptualised in \cite{7}. Humans carrying mobile devices not only act as participatory or “social sensors”, gathering data, but they also interact with the physical and cyber worlds to accomplish changes. Thus, the dynamics of human behaviours play a key role in better understanding the complex behaviour of the cyber-physical-human world, putting people at the centre of this novel IoP paradigm. However, since participating in the sensing systems may incur costs and risks, common individuals are unwilling to participate and feed the system with their sensed data due to the lack of sufficient incentives or pushes towards cooperation. Consuming computational and communication resources of the personal smart devices, or privacy-related issues concerned with the provided location information when collecting data, are only some of these risks/costs. It becomes therefore crucial to motivate users with incentive mechanisms \cite{3, 8, 9, 10, 1}, encouraging them to provide their sensing contributions in a timely and reliable manner. It is important to observe how both the number (i.e., quantity) and the accuracy (i.e., quality) of reports assume a key role in the operational reliability of a MCS application \cite{1}.

In this context, we propose a game-theoretic methodology in order to define the core of a decision support system for the design of a novel incentive mechanism. Its definition is based on some statistical measures, that is the Quality of Information (QoI) and the reputation scores of each user in the network. These estimators are derived from the evolutionary dynamics of human sensing behaviours on a multi-layer social sensing framework, where we quantify the impact of homophily, network heterogeneity and multiplexity. Indeed, by exploring the evolutionary dynamics of human cooperation, we detect which
configurations of social dilemmas and network structures lead to the emergence and resilience of cooperation in a complex network scenario. We therefore define a model which is both data-driven and model-driven. Indeed, starting from data related to different MCS services, we can estimate the statistical measures and define a novel incentive mechanism. On the other hand, from a model perspective, the proposed model defines a class of models, that can be adapted and refined according to specific rules and metrics. Furthermore, by considering human factors and a game-theoretic approach, the proposed methodology aims to make an MCS system increasingly efficient, resilient and adaptive.

1.1. Contributions of this Paper

Once explained the motivations behind the proposed methodology, the main contributions of the paper are summarised below.

- We redesign the problem of incentive mechanism by introducing a novel game-theoretic methodology. It allows us to model and quantify the evolutionary dynamics of human sensing behaviours.

- We define a multi-layer social sensing framework to explore and quantify the dynamics patterns of interactions due to multiple layers, inter-layer coupling and communicability. We also quantify how the evolution of cooperation hinges on the number of layers.

- We measure the joint impact of network properties and human-related factors, such as homophily, in the evolutionary dynamics. To this aim, we define weighted connections between nodes, where weights are defined by taking into account both the concept of homophily and centrality measure in the multiplex structure. We point out how these weights influence behaviours on the multi-layer social sensing framework.

- In order to understand the role of network structural heterogeneity on the evolution of human cooperation, we therefore explore and quantify how the various network structures with a different degree of heterogeneity impact on the evolutionary dynamics of users’ sensing behaviours. We detect how and to what extent some specific network structures and games lead to the emergence and sustainability of cooperation in a complex network scenario.

- We analytically define novel statistical estimators related to truth-worthiness, that is the Quality of Information (QoI) and the reputation scores of each user in the network. These statistical measures constitute the core of Decision Support System (DSS) on which the design of incentive mechanisms is based.

The remainder of the paper is organised as follows. Section 2 summarizes recent literature works on the various aspects considered in our work. Section 3 deals with the novel social game-theoretic methodology proposed in this work. Section 4 presents the simulation analysis and results. Section 5 concludes the paper with directions of future research.
2. Related Work

Recent literature works have shed light on the role of network heterogeneity, homophily, providing also some key insights on how and when cooperation emerges and sustain in the network considering the different social dilemmas. In this section, we review the existing works, other than some proposed game-theoretic models used to design socially-aware incentive mechanisms in MCS.

2.1. Multiplexity, Homophily, Heterogeneity and Social Dilemmas in the Evolution of Cooperation

Relationships between individuals and users are typically multi-relational in nature, so that social behaviours and their dynamics can be understood only by taking into account more than a single network of interactions between them. For this reason, in recent years multi-layer networks [11, 12, 13] have been introduced and regarded as the most suitable way to describe social networks or transportation networks, only to cite a few examples. In multiplex networks, social interactions occur on different contexts and social environments (e.g., family, friendships, colleagues, etc.) and an individual’s behaviour can be different on each layer, although it is determined from the simultaneous interactions on all the layers of the multiplex structure [11, 14, 13, 12, 15]. In a MCS systems, the multiplexity of social interactions of human users carrying their devices therefore adds a further level of complexity. Indeed, other than intra-layer relationships on each single network (or layer), we need to encompass also the inter-layer interactions between humans and their counterpart nodes on the other layers of the multiplex structure. Only by studying the inter-layer interactions between nodes, it is possible to detect the emergent behaviours and focus on the key features related to nodes and edges, from which these patterns are generated [13]. Evolutionary Game Theory (EGT) constitutes the most common framework adopted to face with the conundrum of human cooperation and social dilemmas are typically used as general metaphors for studying the evolution of cooperation [16, 11]. Social dilemmas describe all the conflict situations where the strategy with the highest individual fitness does not represent the most convenient strategy in terms of social community [17]. Thus, players and the whole society would benefit more from mutual cooperation, yielding both an individual and total benefit higher than that of mutual defection. Even though cooperation should not emerge under these conditions, in nature and real-world networks we can observe how the cooperation does exist. One of the main targets of the work is to better understand which are the underlying mechanisms in terms of network structure and human-related factors driving cooperation in a networked scenario.

Homophily is the principle for which similarity breeds connection, namely the tendency to associate and interact more frequently with similar people, as extensively explained in [11, 14, 13]. In terms of evolutionary dynamics of human cooperation, in [11] authors have demonstrated how homophily plays a key role in shaping human behaviours, by guiding and speeding up the emergence
of cooperation between individuals. In a multi-layer network, homophily represents the degree correlation of two nodes on different layers, and it may become a key factor in guiding social behaviours. Thus, so far the role of homophily in the evolution of cooperation on a social multiplex network has been explored and quantified considering only a Scale-Free (SF) network topology and a fixed number of layers [11]. Indeed, real-world populations are heterogeneous, so that there are some individuals (i.e., hubs in a SF network) having many more connections than others.

Some other literature works [18, 19, 20] have unveiled how network heterogeneity plays a key role in the evolution of cooperation as it enhances the emergence and resilience of cooperation. They have demonstrated how the sustainability of cooperation is simpler to achieve in heterogeneous rather than in homogeneous populations, regardless the social dilemma considered as a metaphor for investigating human cooperation. In the field of multiplex networks there are a few results about the role of multiplexity and structural heterogeneity on the evolution of cooperation [10, 21]. It is important to note that their results have been derived in most cases by using the mean-field hypothesis and assuming there is no correlation between the strategies used by an individual in each layer of the multiplex [10]. Instead, in our work, we include correlation between nodes strategies on different layers, which depends on the communicability function and inter-layer coupling and interdependence between layers [11, 22]. Moreover, since the layers of a multiplex structure may exhibit a different network topology and degree of heterogeneity, in this work we explore and quantify how the various network structures with a different structural heterogeneity impact on the evolutionary dynamics of users’ sensing behaviours.

In [21] the authors have systematically studied the evolution of cooperation in four social dilemmas that we also consider in the T-S plane on the multiplex network. They found out some features in the microscopic organisation of strategies, that are responsible for the important differences between cooperative dynamics in monoplex or single-layer networks and multiplex networks. Moreover, some works have demonstrated how the extent of multiplexity, which hinges also on the number of layers and inter-layer coupling measure between them affect the emergent social dynamics on the multiplex network [21, 10, 11]. Also, the role of homophily may result different according to the underlying network structure of each layer and the number of layers composing the multiplex structure. It is important to note that in their work authors have considered that each layer is a homogeneous graph (i.e., Erdős-Rényi (ER)) and they have adopted the replicator-like rule for the nodes strategy update. Differently from [21], we take into account various network structures (see 3.2), exhibiting a different structural heterogeneity, and the Fermi rule as microscopic strategy update rule (see 3.2.1). Some other authors [23] have analysed the evolutionary dynamics of various social dilemmas, deriving Nash equilibria before under the hypothesis of well-mixed population and then considering a ER-structured population. In the latter, they have distinguished between an interaction network and an updating network, thus separating the role of layers in the multiplex structure. In our work, we do not separate the role of layers in the multiplex
structure and in addition we measure the impact of network heterogeneity and homophily (see [3,1]). From literature works, it is clear how there are some unsolved questions in the field of evolutionary dynamics of human behaviours on a social multiplex network. Indeed, in the hypothesis of considering a structured population, where nodes interact with their neighbours on each layer of the multiplex network and on each layer of the multi-layer sensing framework, we will answer to the following question: what is the joint impact of network heterogeneity, homophily and multiplexity on a structured population in terms of evolutionary dynamics of human sensing behaviours?

2.2. Game-theoretic and Socially-aware Incentive Mechanisms

Most of the incentive mechanisms used in CS applications are aimed at stimulating the degree and regularity of contributions. Overall, the factor mainly used to decide how to disburse incentives is therefore related to “quantity” (i.e., degree of participation), without taking into account the “quality” of information, that is the accuracy or truthfulness of contributions [1, 24]. As underlined in [1], we must take into account both aspects, since false contributions may result in publishing wrong information, dramatically influencing the service operation. Thus, it becomes essential to measure the Quality of Information (QoI) related to users’ contributions and then derive a user reputation score of each human user in the MCS application.

Some recent works have proposed game-theoretic models and socially-aware incentive mechanisms in MCS scenarios in order to analyse and increase the participation level of users, also including social network effects [3, 25, 26, 27]. However, none of them has ever included multiplexity and homophily and a game-theoretic model targeted at exploring human cooperation on a multiplex social sensing by analysing the role of the various social dilemmas and complex network topologies. Various approaches based on game-theoretic models have addressed the issue of strategic participation of users in a MCS application [1, 28]. Recently, in [24] authors have proposed to consider also the social structure information and influence between users in a socially-aware Bayesian Stackelberg game to explore the users’ participation level. Then, they introduce a backward induction to propose an optimal incentive mechanism of the crowdsensing service provider. Also in other works [26, 27] it has been investigated how to exploit the social network effects and trust to encourage users’ participation through reciprocity, so that crowdsensing service providers obtain a greater gain. In most of the CS incentive schemes, auctions and pricing strategies provide incentives to mobile users to participate in crowdsensing applications and the basic idea is to either maximize the total utility/value of the sensing platform under certain costs/budgets constraints or minimize the total disbursement of the platform.

Nevertheless, some of the main drawbacks of the proposed game-theoretic models are mostly related to the lack of a dynamic modeling approach, the rationality assumption of agents and they overlook the selfish or malicious nature of human users. To deal with these issues and challenges, in the proposed modeling approach, we propose a model for MCS which is inherently dynamic. Indeed, we evaluate the evolutionary dynamics of human sensing behaviours through
the rounds of iterated social dilemmas following a microscopic strategy update rule based on a Fermi statistical distribution (see subsection 3.2.1). Thus, the evolutionary game-theoretic approach does not require players/human users to act rationally, but they only choose a strategy at each round of the game trying to maximize their payoff \[11\]. In the next section we will describe the proposed social game-theoretic model.

Figure 1: Social Sensing and Cognitive architecture. The figure schematically describes the various steps and aspects of the modeling procedure. Starting from IoP and the definition of the multi-layer social sensing framework of services and weighted weighted social multiplex network of users (first block), we quantify the evolutionary dynamics of human sensing cooperation through game-theoretic modeling (second block). Then, after quantifying the emergence and sustainability of cooperation on various network topologies and by varying homophily between nodes on the network, we define the core of a DSS aiming at designing socially-aware incentive mechanisms (see text).

3. Social Game Theory

The modeling approach is schematically described in Fig. 1. In the first block, starting from IoP we derive the multi-layer social sensing platform, where layers represent the various services but, at the same time, we define also the weighted multiplex social sensing between users, where weighted relationships are those among users and layers are the various channel of social interaction. The second block is the game-theoretic modeling where, starting from weighted social multiplex network, we explore social interactions between users and model the evolutionary dynamics of human sensing behaviours. We quantify the emergence and sustainability of cooperation by varying the network topologies, homophily and multiplexity. Once detected the games and network topologies
leading to the emergence and sustainability of cooperation, we analytically define and measure the QoI and the users’ reputation scores in the network. Thus, based on these measure, we define the core of a DSS targeted at designing proper socially-aware and dynamic incentive mechanisms. In this section we describe each block of the framework.

3.1. Multi-layer Social Sensing and Homophily

Let us consider a multiplex network of $M$ layers, $\alpha = \{1, ..., M\}$, and $N$ nodes, $i = \{1, ..., N\}$, which is a set of $M$ networks $G_\alpha = (V, E_\alpha)$. The set of nodes $V$ is the same for each layer, whereas the set of links $E$ changes according to the layer. Each entity or node in the weighted multiplex social sensing network is a human user with a different contribution profile and interacting with other users. Fig. 2 describes the multi-layer social sensing modeling approach adopted in this work.

In a MCS environment, layers represent various services exploited by the users, and the multi-layer interactions may affect users’ sensing behaviour, and their choice to actively and qualitatively contribute (i.e., cooperate) to the sensing process. Thus, the proposed MCS multi-layer modeling approach is dual: since it is both an IoP-based weighted multiplex social sensing, in terms of

![Figure 2: Multi-layer Social Sensing and inter-layer coupling on a Weighted Multiplex Social Sensing.](image)
weighted interactions between users, and a multi-layer social sensing platform, in terms of services (see Fig. 2). Indeed, users, while providing and sharing information on various services (see Fig. 2 (a)), interact on the social multiplex network changing their behaviour towards other users in the network and the whole MCS application (see Fig. 2 (b)), thus impacting on the reliability and operation of various services. The aggregated layer conveys all the structural information contained in the multi-layer social sensing. In Fig. 2 (b) we show the importance of considering the dynamic patterns of connectivity deriving from the coupling between layers of the social multiplex network. Multiplex networks inherently include the concept of heterogeneity [14, 29], both structurally, in terms of various types of interactions on multiple layers, as well as in terms of contributors’ profiles, that is the different behaviours in all the layers of the multiplex structure. To characterize and measure such heterogeneity, we define a weight for links between nodes at each layer, so that we consider a weighted multiplex social network, where human behaviours are the result of multi-scale social interactions on such networks [13, 12]. Weights’ definition is based on a combined measure of eigenvector-like centrality and homophily, as defined in [11]. The eigenvector-like centrality measure includes the concept of influence in our analysis. Its definition is based on the spectral properties of the adjacency matrix of each layer of the multiplex network. It allows us to take into account not only the number of links of each node, but also the quality of such connections. Central nodes are the most influential nodes which can influence the behaviours of their neighbouring nodes.

In our model, other than considering a structural property of network represented by centrality, weights of interactions between human users at each layer of the multiplex structure are defined according to the homophily measure \( h_{ij} \). In particular, homophily has a dual definition. On the one hand, it is an interaction-based measure, depending on the frequency of interactions between users on various social channels of interactions in the weighted multiplex social sensing. Thus, the more they interact on the social multiplex network, the higher will be the homophily measure between them. On the other hand, it is also a similarity-based measure, which takes into account the different dimensions of homophily, along with the actions on MCS services, to derive an Euclidean distance between human users. Overall, by considering both the definitions, we can define the concept of homophily as follows:

**Definition 3.1.** Homophily, denoted as \( h_{ij} \), is a measure of similarity between two nodes/human users \( i \) and \( j \), so that:

\[
h_{ij} = \frac{1}{1 + \delta_{ij}}
\]

where \( \delta_{ij} \) is the homophily difference (or distance) between users \( i \) and \( j \) [11].

3.2. Game-Theoretic Modeling - Social Dilemmas and Network Structures

In order to quantify and capture the social dynamics of human users’ behaviours on the social multiplex network, we introduce an evolutionary game-theoretic (EGT) approach. This allows us to obtain a multi-scale analysis of
social dynamics and derive the impact of multiplexity on the users’ sensing attitude in MCS applications. In particular, we focus on exploring the evolution of cooperation, intended as the emergence and sustainability or resilience of cooperation on the multiplex network.

In the analysis of human sensing cooperation through EGT, we exploit different social dilemmas where, although these are all two-strategies games, each of them has a different characterisation, reflected by the specific payoff matrix representing its rules of interactions. Hence, social dilemmas allow us to analyse different conflict situations and evaluate how each of them yields distinct Nash equilibria and significant changes in game dynamics. It is important to observe how a social dilemma is a game which possesses at least one socially inefficient Nash equilibrium. In particular, we consider the iterated forms of the Prisoners Dilemma game (PD), the Snowdrift Game (SD), the Stag-Hunt game (SH) and the Harmony Game (HG). In these social dilemmas, agents/players are the users of a MCS system that, can choose between two strategies: cooperate (C) or defect (D). Cooperating means honestly contributing and participating to the sensing task, such that human user decides to pay a cost of providing his contribution. In order to have a high operational reliability in a crowdsensing application and have a robust Quality of Information (QoI), also the other player should contribute. 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 a selfish way. In this case, if also the other player decides to defect, the task will not be accomplished with a negative effect for both players. A game can be defined in function of its payoff matrix as in Table 1. Players will both receive a reward $R$ in the case of mutual cooperation or a punishment $P$ in the case of mutual defection. A defector will get the temptation payoff $T$ when playing against a cooperator, while the cooperator obtains the so-called sucker payoff $S$. The difference between the above defined social dilemmas lies in the ranking of payoffs. In the PD, the payoffs are ordered as $T > R > P > S$, meaning that the defection is the best strategy irrespective of the opponents decision [21]. SD is an anti-coordination game where the payoffs’ ranking is the following: $T > R > S > P$, so that it evolves towards the coexistence of both cooperators and defectors. Instead, SH is a classical example of coordination game and the ranking is as follows: $R > T > P > S$. Finally, in the HG the ranking is: $R > S > P$ and $R > T > P$. Overall, the final state of a population playing the HG game will be total cooperation, regardless of the initial fraction of cooperators, the opposite of PD. Moreover, each of the

|   | C | D |
|---|---|---|
| C | R | S |
| D | T | P |
layers of the social multiplex network is a complex network that is represented by an underlying graph where nodes are connected according to a network topology [30]. Among them we consider the most investigated network topologies or structures: random graphs network models, such as the Erdős-Rényi (ER) model [31], the small-world (SW) networks, such as the Watts-Strogatz model [32], and the Scale-free (SF) networks [33]. We therefore take into account network structures exhibiting a different level of heterogeneity. ER graphs are homogeneous networks, where nodes have the same degree, so that there is a uniform probability to be connected (no degree correlations between nodes in the network) and the degree distribution could be approximated by using the Poisson distribution. SW networks are small heterogeneous networks, characterised by a high clustering and modularity, so that there are groups of nodes that are more highly connected than the rest of the network, and there is an over-abundance of hubs (high-degree nodes) that mediate the shortest path length. In SW networks, degree distributions exhibit a fast typically Gaussian decaying tail. Finally, SF networks are highly heterogeneous networks, characterised by a power-law degree distribution. They exhibit a high degree correlation between nodes and degree distribution has a long tail, which means that there are a few hubs in the network.

3.2.1. Evolutionary Dynamics of Human Sensing Behaviours

To explore and quantify the evolutionary dynamics of human sensing behaviours on the social multiplex network, we take into account the iterated forms of the above-described pairwise social dilemmas (see 3.2, where at each round of the game human users can change their strategies or behaviours, based on imitation dynamics of the fittest strategies [11, 17]. We quantify and simulate the evolutionary process in accordance with the standard Monte Carlo simulation procedure, composed of elementary steps, as in [11, 17, 34], so that at each round a player $i$ changes its strategy $S_i$ and adopts the strategy $S_j$ from player $j$ with a probability determined by the Fermi function, defined as follows [11]:

$$W(S_j \rightarrow S_i) = (\eta_i) \cdot \frac{1}{1 + \exp((P_i - P_j)/ (\delta_{ij} \cdot K))} \quad (2)$$

Therefore, a player $i$ adopts the strategy $S_j$ of another player $j$ in function of the payoff difference $P_i - P_j$, and according to $\delta_{ij}$ and $\eta_i$ values. Specifically, $\delta_{ij}$ is the homophily difference between two human users, so that if this value is low, a player $i$ is more likely to imitate the strategy of $j$ at each round (see 3.2.2). $K$ is the selection intensity and quantifies the uncertainty in the strategy adoption process and it is defined as in [11]. $\eta_i$ is the scaling factor defined according to the communicability function between layers of the multiplex structure [11, 22]. It is introduced to include the dependency of the strategy adopted by the player $i$ on the strategies adopted by the counterpart nodes and its neighbours on the other layers [11]. Thus, $\eta_i$ points out the coupling between layers ($\omega_{xy}$) in the investigation of the evolution of human sensing behaviours on the multiplex structure and it may result in a bias regarding the strategy adoption of the
player $i$ in the subsequent round of the game. Specifically, the scaling factor $\eta_i$, is defined as follows:

$$\eta_i = 1 - \left( \eta_{i_{\text{max}}} - \eta_{i_{\text{min}}} \right) \frac{\sum_{j \in \beta, S_i = S_i} [G_{\alpha \beta}]_{ij}}{\sum_{j \in \beta} [G_{\alpha \beta}]_{ij}},$$  \hspace{1cm} (3)$$

where at the numerator there is the sum of the communicability functions calculated between the node $i$ on the layer $\alpha$ and all its neighbouring nodes $j$ on the layer $\beta$, adopting the same strategy as player $i$. The denominator represents the sum of the communicability functions calculated between the node $i$ on the layer $\alpha$ and all its neighbouring nodes $j$ on the layer $\beta$.

### 3.2.2. Communicability function

Overall, the factor $\eta_i$ enables us to measure the effect of inter-layer coupling and influence between a node/player and its replica on the other layers. Thus, we leverage the definition of communicability function provided in [22], which quantifies the number of possible routes that two nodes $i$ and $j$ in the multiplex have to communicate with each other. Therefore, considering a multiplex network consisting of $M$ layers, denoted by $L_1, L_2, ..., L_M$, and their respective matrices $Z_1, Z_2, ..., Z_M$, representing the Hadamard product between the homophily matrices and the adjacency matrices of the multiplex $M$, its matrix is then given by: $\mathcal{M} = Z_L + C_{LL}$, where $Z_L$ is defined as follows:

$$Z_L = \bigoplus_{a=1}^{M} Z_{\alpha} \hspace{1cm} (4)$$

and $C_{LL}$ is a matrix describing the inter-layer interaction, defined as follows:

$$C_{LL} = \begin{bmatrix}
0 & C_{12} & \cdots & C_{1M} \\
C_{21} & 0 & \cdots & C_{2M} \\
& \vdots & \ddots & \vdots \\
C_{M1} & C_{M2} & \cdots & 0
\end{bmatrix} \in \mathbb{R}^{NM \times NM} \hspace{1cm} (5)$$

where each element $C_{\alpha \beta} \in \mathbb{R}^{N \times N}$ represents the interaction of layer $\alpha$ with layer $\beta$. Here it is assumed that we have a symmetric interaction between layers, that is: $C_{\alpha \beta} = C_{\beta \alpha} = C = \omega_{\alpha \beta} I = \omega_{\beta \alpha} I$, for all layers $\alpha$ and $\beta$. $\omega$ is the parameter describing the strength of the inter-layer interaction, and $I \in \mathbb{R}^{N \times N}$ is the corresponding identity matrix. So we can now write the multiplex matrix as follows:

$$\mathcal{M} = \begin{bmatrix}
Z_1 & \omega_{12} I & \cdots & \omega_{1M} I \\
\omega_{21} I & Z_2 & \cdots & \omega_{2M} I \\
& \vdots & \ddots & \vdots \\
\omega_{M1} I & \omega_{M2} I & \cdots & Z_M
\end{bmatrix} \in \mathbb{R}^{NM \times NM} \hspace{1cm} (6)$$

As we are interested in accounting for all the walks between any pair of nodes in the multiplex, we take into account the number of walks of length $k$ between two generic nodes $i$ and $j$ in the multiplex, which is given by the $\alpha, \beta$-entry of
the $K$-th power of the adjacency matrix of the network. Hence, the walks of $k$ length in the multiplex are given by the different entries of $\mathcal{M}^K$. These walks can include both intra- and inter-layer hops [22] and we are interested in giving more weight to the shortest walks than to the longer ones.

The communicability between two nodes $i$ and $j$ in the multiplex network is defined as the weighted sum of all walks from $i$ to $j$ as follows:

$$G_{ij} = I + \mathcal{M} + \frac{\mathcal{M}^2}{2!} + \ldots = \sum_{k=0}^{\infty} \frac{\mathcal{M}^k}{k!} = \exp(\mathcal{Z}_L + \mathcal{C}_{LL})|_{ij}$$ (7)

We can now define the communicability matrix $G$, where each element $G_{\alpha\beta} \in \mathbb{R}^{N \times N}$ is the matrix representing the communicability between each pair of nodes belonging to two different layers $\alpha$ and $\beta$, of the multiplex $\mathcal{M}$. It is defined as follows:

$$G = \exp(\mathcal{Z}_L + \mathcal{C}_{LL}) = \begin{bmatrix}
G_{11} & G_{12} & \ldots & G_{1M} \\
G_{21} & G_{22} & \ldots & G_{2M} \\
\vdots & \vdots & \ddots & \vdots \\
G_{M1} & G_{M2} & \ldots & G_{MM}
\end{bmatrix}$$ (8)

where $G \in \mathbb{R}^{NM \times NM}$ and $[G_{\alpha\beta}]_{ij}$ represents the communicability between the node $i$ on the layer $\alpha$ and the node $j$ on the layer $\beta$.

3.3. Statistical Measures for Designing Incentive Mechanisms - QoI and User Reputation Score

In order to design a novel incentive mechanism, we need to define some statistical estimators related to users’ behaviour. Thus, starting from the quantification of human users’ behaviour, we introduce a novel measure of reputation score based on human users’ behaviours in the multi-layer social sensing. The reputation score for each individual is calculated as a function of the quality and quantity of data provided by the individual [1]. In order to define the user reputation score for each human user, first we quantify the ‘social honesty’ of each individual, by defining the statistical estimator $\gamma_i$ as follows:

$$\gamma_i = \sum_i (NC)_i / (N_r * N_{nb}),$$ (9)

where $NC_i$ is the number of cooperative behaviours of node $i$ over the $N_r$ rounds of the game. $N_{nb}$ is the number of neighbours for each node $i$. Thus, $\gamma_i$ quantifies the level of cooperativeness of each user in the network, considering its behaviour against neighbourhood and it allows us to classify the contributors in honest, selfish or malicious users [1, 15]. Here $\gamma_i$ ranges in $[0, 1]$ such that $\gamma_i = 0$ reflects a lack of cooperativeness, while $\gamma_i = 1$ means that a human user has been fully cooperative with a proactive attitude towards its social community and neighbourhood. By averaging this measure over the population, we get an overall measure of QoI in the network structure, defined as follows:
\[ QoI = \gamma_i^{av} = (1/N) \sum_i \gamma_i \] (10)

The user reputation scores \( RS_i \) for each user \( i \) are given by the ratio between the local measure of \( \gamma_i \) for each node averaged over the global attitude of users in the network, given by the QoI measure, so that it is defined as follows:

\[ RS_i = \frac{\gamma_i}{\gamma_i^{av}} = \frac{\gamma_i}{QoI} \] (11)

The statistical estimator \( RS_i \) quantifies and relates the importance of the contribution given by the user as compared with the overall QoI in the network. Table 2 sums up all the statistical estimators and parameters defined in our model.

| Estimator | Physical meaning/Definition                        |
|-----------|---------------------------------------------------|
| \( h_{ij} \) | Homophily between nodes \( i \) and \( j \)       |
| \( \delta_{ij} \) | Homophily difference (distance) between nodes \( i \) and \( j \) |
| \( \eta_i \) | Scaling factor depending on the communicability function |
| \( P_i \) | Payoff obtained by the player \( i \)          |
| \( P_j \) | Payoff obtained by the player \( j \)          |
| \( S_i \) | Strategy chosen by the player \( i \)         |
| \( S_j \) | Strategy chosen by the player \( j \)         |
| \( \gamma_i \) | Social honesty of the player \( i \)        |
| \( QoI \) | Quality of Information                           |
| \( RS_i \) | Reputation Score for each user \( i \)       |

Table 2: **Statistical estimators of the model.** We include the definition and physical meaning of the different statistical estimators/parameters of the model (see Text).

4. Results

In our model, we aim at evaluating and quantifying the role of homophily, network heterogeneity and multiplexity in the emergence and sustainability of cooperation on the social multiplex network of human users. Thus, the first target is to derive the density of cooperators at steady-state in the network. To this aim, simulations have been conducted choosing a social multiplex network with \( M \) layers (where the number of layers has been varied) and \( N = 200 \) nodes or human users, where each layer is modeled as one of the network structures. Homophily values are randomly chosen following a normal distribution around a mean value, with standard deviation \( \sigma \). The target has been to analyse the joint effect of all these aspects in the evolutionary dynamics, detecting those configurations of network structures and social dilemmas more able to make the cooperation among human users propagate and sustain in the network.

4.1. Density of cooperators

Fig. 3 shows the evolution of cooperation, namely the density of cooperative nodes against the rounds of the game. We have simulated the evolutionary dynamics in all the possible configurations of social dilemmas and network
Figure 3: **Density plots.** The figure illustrates the density of cooperation in various network configurations and social dilemmas (a-h). The colour corresponds to the density $\rho$, ranging from ‘blue’ (lowest) to ‘red’ (highest). We show the following configurations of network structure and game: (a) SF-HG; (b) SF-PD; (c) SF-SH; (d) SW-SH; (e) SW-PD; (f) ER-PD; (g) ER-SD with $M = 2$ layers; (h) ER-SD with $M = 7$ layers.
topologies, also varying the number of layers, for a number of rounds such that a dynamical steady-state was reached. We can observe how the SF is the most suitable network topology for the emergence of cooperation (see (a)-(b)-(c)). Instead, both in the ER and SW networks, there is a mixed equilibrium with a coexistence of both strategies. More specifically, in the SW network topology, in both cases of SH and PD, we can see the coexistence of both strategies with a prevalence of defectors at equilibrium (see (d)-(e)). The emergence of defection is more marked in the PD rather than in SH, as expected considering the defecting nature of PD. While in the ER network configuration, when PD is played between human users, at the beginning we can observe the prevalence of defectors and a coexistence of the two strategies at equilibrium (see (f)). Finally, the last two plots related to ER network and SD (see (g)-(h)) allows us to highlight the role of the number of layers in the evolutionary dynamics of behaviours. In particular, as in [21] [16], an increase in the number of layers results in a stronger emergence of cooperation on the social multiplex network, as indicated by the higher density of 'red' points at equilibrium.

This result is what we expected by reasoning in terms of connectivity patterns of the different structures and it is related to the nature of the SF network topology compared with ER and SW networks. Indeed, SF is inherently heterogeneous, strictly resembling real-world networks displaying a skewed statistical distribution deriving from the preferential attachment rule (“rich-get-richer”) [33]. The evolutionary dynamics observed in the case of SW structure derives from its high clustering coefficient of a node with its neighbours, thus bordering the cooperation within communities.

Comparing the two SF cases (a) and (b), we clearly observe the difference related to the game played by users, where HG produces a higher density of cooperation than in the SH, as expected from literature [21]. Thus in the SF case, although in all social dilemmas we can notice the emergence of cooperation, HG and SD are the most cooperative dilemmas at evolutionary equilibrium and those more able to sustain cooperation over time. This is even more marked in the high homophily case ($\sigma = 1$), where we note a faster emergence of cooperation, rather than in the low homophily case ($\sigma = 8$), as expected from [11] [17].

4.2. Colour maps

By digging deep into the impact of games along with the various network topologies, in Fig. 4 we show the density of cooperators in the T-S plane, where each of the quadrants correspond to a different social dilemma. Generally, T-S plane allows us to show and better understand what happens in terms of evolutionary dynamics by varying the values of temptation and sucker’s payoffs of the different social dilemmas. Furthermore, it allows us to visualize and bring out the transitions areas between the different density levels of cooperation for each network structure and game. In (a) and (b) we show the most cooperative topology, namely the SF, in both cases of low and high homophily. Despite the different dynamics observed for the different games, in the high homophily case there is a major density of cooperators rather than the low homophily case. Below we discuss the results for each quadrant of the colour maps.
The HG (upper-left quadrant), where cooperation is its dominant strategy, results in the most cooperative game, since we see the higher emergence and resilience of cooperation compared with the other dilemmas, even when choosing high values of temptation payoff \( b \). The SD (upper-right quadrant) is an anti-coordination game characterised by a stable equilibrium in mixed populations. Thus, we observe the coexistence of both strategies at equilibrium, also varying the values of temptation and sucker’s payoffs. In this game the role played by homophily is more evident, since by increasing homophily we see a higher density of cooperation in the T-S plane. In the SH (lower-left quadrant), there is an unstable evolutionary equilibrium with mixed populations. As in the SD case, we have the coexistence of both strategies, even if the density of cooperation is on average lower than SD. Analogously to SD, we can see the increase of density of cooperative nodes according to homophily values. In the PD (lower-right quadrant), defection dominates cooperation, but by comparing the PD in the
two cases of low and high homophily, we can see how homophily allows cooperation to emerge. This is more clear for low values of $b$ (e.g., $b = 1$), which is equal to the temptation payoff in the PD, and for values of $c$ that tend towards zero. In the case of PD, an increase of temptation ($b$) and a decrease of sucker’s payoff values (since, by increasing $c$ values, we have lower sucker’s payoffs, which is equal to $-c$, which means a major cost of cooperating), yield an increasingly lower density of cooperators (see the lower-left corner of the PD quadrant). In (c) and (d) we show the density of cooperators in the ER and SW networks. By looking at the density of cooperation in the T-S plane resulting from both these network structures, the previously discussed inherent properties of each game are even more marked than in SF network. Indeed, from one hand we can easily see the high cooperativeness of HG (upper-left quadrant) and vice versa the high density of defecting users in the PD (lower-right quadrant). On the other hand, we can observe how in both SD and SH, we have the coexistence of mixed strategies.

4.3. The role of Network Heterogeneity

Our results shed light on the importance of network heterogeneity, as it induces cooperative agents (or nodes) to create assortative clusters, where they reciprocate cooperation. This mechanism is known as network reciprocity, and it represents one of the five mechanisms ruling the cooperation between individuals [35, 36]. The main underlying principle is that the benefit produced by cooperating outweighs the cost of cooperating with all neighbours. In particular, by denoting with $r$ the benefit-to-cost ratio (or game return), so that: $r = b/c$, we have that the fixation of cooperation through network reciprocity occurs only if it is satisfied the following condition: $r = b/c > \langle k \rangle$, where $\langle k \rangle$ is the average degree in the network (the average number of neighbours). The average degree: $\langle k \rangle = \frac{1}{N} \sum_{i=1}^{N} (k_i)$ gives information about the network sparsity, but it does not provide any information on the degree distribution, which is instead the discriminant of each network topology. For this reason, it is crucial to dig deep into the microscopic and mesoscopic issues of cooperation, better explaining how the cooperation evolves [19]. There are mainly three types of players: mixed players (players that change their strategy as the evolutionary process runs), pure defectors and pure cooperators (players that never change their strategy). The organisation of these players is worthy because always exists a boundary of mixed players between pure cooperators and pure defectors. At the mesoscopic level, the community structure of the network typical of many real social networks, has been demonstrated to be important in the preservation of cooperation under heavy temptation to defect conditions. Reasoning in microscopic terms, as also underlined in [18], the stability of cooperation in the network structure depends on being more in contact with nodes having different and fluctuating strategies and not with the clusters of defectors. The cluster of cooperators is stable if none of its composing nodes has a defector neighbour coupled to more than $N_C/b$ cooperators, where $N_C$ is the number of cooperators linked to the player. This becomes even more challenging for cooperation to evolve if these connections between a cooperator and a defector neighbour
occurs with a high homophily between that nodes. The main difference between the considered network structures in microscopic terms is related to the distribution and composition of the clusters of cooperators and defectors. Indeed, in the case of ER graphs, looking at Figs. 3 and 4 there is a wide region of temptation payoffs with a coexistence of the two strategies, and this is due to the presence of several small clusters of cooperators. This fragmentation of pure cooperators into several clusters of cooperators merged into a region of fluctuating individuals, makes these clusters more exposed to invasion. Instead, in SF networks pure cooperators form more compact clusters, that follow hubs behaviours, and finally merging them in a big group or main cluster. The formation over the rounds of games of only one big group of cooperators makes them more resilient to defection as the number of pure cooperators exposed to fluctuating individuals is lower. High homophily values further speed up the process of group (or cluster) formation and also the size of the single cooperative group in the SF network [11], enhancing the network resilience against an invasion of defectors. In SW networks, there is also a continuous formation of compact clusters of cooperators, due to the high clustering coefficient of SW network. However, these clusters in the network hinder the evolution of cooperation and its fixation in the whole multiplex structure due to the lack of weak ties between groups or cluster of cooperators. Thus, cooperative behaviours remain bounded within clusters, since cooperators in the clusters are less connected to the surrounding network, reducing the probability for a widespread propagation. This is due to the inherent nature of SW networks, having only a small heterogeneity and not highly connected hubs. Moreover, it is important to note how the results in terms of evolutionary dynamics of behaviours for the different games are coherent with those obtained in [21, 16, 11]. In addition, we have analysed and quantified the impact of different network topologies (SF, ER, SW) and the role of homophily, shedding light on its impact on the evolution of cooperation in the various social dilemmas. Results confirm how homophily acts as a shaping factor of cooperation, able to increase the density of cooperation in all the evolutionary games [11, 17].

4.4. Local and global Nash equilibrium points - Homophily and Heterogeneity

Starting from the previous considerations, related to the various games, network heterogeneity and homophily, in this section, following [37], we define local and Nash equilibria points in our model. Nash equilibrium represents a key concept in game theory, as it suggests the possible outcomes when different players play simultaneously in order to maximise their payoff. The idea behind equilibrium is that if the players choose strategies that are best responses to each other, then no player has an incentive to deviate to an alternative strategy [38]. In evolutionary settings (EGT), the concept of Nash equilibrium consists of the Evolutionarily stable strategy (ESS). Thus, the equilibrium is a stable distribution of strategies, namely a genetically-determined strategy that tends to persist once it is prevalent in a population [38].

In the case of structured population, such as a social multiplex network, interactions are spatially constrained, as nodes and their counterparts interact.
only with their neighbours at various layers of the multiplex structure. At each round a node/player plays with only one neighbour as described in section 3. In our model, links are relatively stable in the whole evolution process, but we change homophily values in order to quantify its impact on different network topologies and games. As showed in density plots (see Fig. 3) and contour plots (see Fig. 4), we observe how the stable states are only three, respectively corresponding to a prevalence of defectors, cooperators and mixed strategies. These stable states are the result of a chain of local Nash equilibria [37], until reaching a global equilibrium. Indeed, the overall population is divided into a few groups playing the same strategy, and the various factors, such as network heterogeneity and specifically homophily, impact on the formation of these groups over the time, both in terms of speed and size [11], as underlined in the previous sections. The higher are the homophily values, the quicker is the formation and size of groups of cooperators, in all the games and specifically their role is more evident in PD and SD games. In other words, we can observe the presence of attractors and a polarisation of strategies mainly focused on defectors and cooperators. Homophily plays a key role in making cooperation percolate through the network, and this is even more marked in a SF network, due to its heterogeneity in the degree distribution as explained in section 4.3.

Since deriving the exact expressions of ESS or Nash equilibria points is extremely difficult due to the difficulty of formulating the replicator dynamics, following [37], we define local Nash equilibria. Then, in order to get the ESS, a chain of local Nash equilibria is suffice to lead the system into the stable state, since in structured population and heterogeneous networks balancing the gap of payoffs between different strategies is not so difficult.

We are going to discuss and define the local Nash equilibrium in structured populations, exploiting the model presented in [37], and extending their definition including homophily and therefore replacing the adjacency matrix $A_{ij}$ with the matrix $Z_{L}$ as in (4).

At each round of the game, a node/player $i$, plays with its neighbours whose number is quantified by the degree centrality $k_i$. In a two-strategy evolutionary game, we can define the strategy of the player $i$ as follows:

$$\Theta_i(n) = \begin{pmatrix} S_i(n) \\ 1 - S_i(n) \end{pmatrix}$$

where $S_i(n)$ can only take values 1 or 0 at the n-th round. For $S_i(n) = 1$, the player $i$ is a cooperator (C), while for $S_i(n) = 1$, player $i$ is a defector (D). Locally, for each player $i$’s gaming environment, we define the local frequency of cooperators at the $n_{th}$ round as follows:

$$\Xi_i(n) = \frac{\sum_j Z_{ij} \Theta_j^T(n) (1)}{k_i}$$

In this scenario, keeping the strategies of the neighbours of the player $i$ unchanged is equivalent to keeping $\Xi_i(n)$ unchanged. For the global gaming
environment, we define the global frequency (or density) of cooperators at the $n_{th}$ round as follows:

$$\rho(n) = \frac{\sum_i \Theta^T_i(n) (1)}{N} \quad (14)$$

where $N$ denotes the population or the number of nodes of the social multiplex network.

In a two-player game, the payoff table is a $2 \times 2$ matrix as in Table 1. Considering equation (12), the payoff of player $i$ at the $n_{th}$ round is given by:

$$P_i(n) = \Theta^T_i(n) \begin{pmatrix} R & S \\ T & P \end{pmatrix} \sum_j Z_{ij} \Theta_j(n) \quad (15)$$

Given eq. (15), $\sum_j Z_{ij} \Theta_j(n)$ can be rewritten as:

$$\sum_j Z_{ij} \Theta_j(n) = k_i \left( \begin{pmatrix} 1 \\ 0 \end{pmatrix} \Xi_i(n) + \begin{pmatrix} 0 \\ 1 \end{pmatrix} (1 - \Xi_i(n)) \right) \quad (16)$$

By including the eq. (12) and eq. (16) into eq. (15), we obtain:

$$\Phi_i(n) = k_i (\Delta_i(n) S_i(n) + T \Xi_i(n) + P (1 - \Xi_i(n))) \quad (17)$$

where $k_i$ denotes the connectivity of node $i$ and $\Delta_i(n) = S - P + (R - T + P - S) \Xi_i(n)$. The maximum of $\Phi_i(n)$ is obtained by considering the best strategy, which is denoted by [37]:

$$S_{i,max}(n) = \begin{cases} 1 & \text{for } \Delta_i(n) > 0 \\ 1 & \text{or } 0 \quad \text{for } \Delta_i(n) = 0 \\ 0 & \text{for } \Delta_i(n) < 0 \end{cases} \quad (18)$$

If two connected nodes $i$ and $j$ choose strategies $S_{i,max}(n)$ and $S_{j,max}(n)$ as their strategies at the $n_{th}$ round, respectively, they are in a local Nash Equilibrium. These two nodes/players are called as “Nash pair”. Then, if all the nodes in the multiplex structure are in the local Nash Equilibrium, the population is in a global Nash Equilibrium. If $\Delta_i(n) = 0$ or $\Delta_j(n) = 0$, this local equilibrium represents a weak local Nash equilibrium. Otherwise, it is a strict local Nash equilibrium. The maximum evaluated in the previous equation depends on the value of $\Delta_i(n)$, that is defined starting from the payoff matrix values. In our model, along with payoffs, also homophily values impact on the strategy adoption through the matrix $Z_{ij}$ matrix. Moreover, local Nash equilibria represent a series of multiple equilibria, whose emergence is ruled by the various factors defined in the model. Each of these local Nash equilibria behaves as an agent, and then reaching a sort of coalescence corresponding to the global Nash equilibrium.

Starting from [37], we redefine a “Nash pair”, which measures the fraction (or density) of Nash pairs in the overall multiplex network, as follows:

$$\alpha = \frac{N_p}{E} \quad (19)$$
Local and global Nash equilibria. In the case of SF network and PD game, figure shows the different phase transitions representing the local Nash equilibria and finally the global Nash equilibrium represented by the overall cooperation in the multiplex structure (see Text).

where $N_p$ denotes the number of the Nash pairs in a network and $E$ denotes the number of edges through the layers of the network. It is important to note that if two nodes have multiple links on the various layers of the multiplex network, in the aggregated network we only consider this connection once. If $k_i = k_j = 1$, the local Nash equilibrium is equal to Nash equilibrium in the classical game theory. As underlined in [37], the parameter $\alpha$ constitutes a tool to evaluate the evolutionary dynamics of behaviours in the multiplex structure is in an evolutionary stable state.

Local Nash equilibria in the structured population are metastable points where sub-populations and groups move towards a stable global equilibrium state over time. This ESS corresponds to the overall cooperation, and its emergence is based on network heterogeneity, the type of game considered and homophily values. The system shows a low multiplicity, a few number of steady states and the variously the different factors allows to reach these states. Even though we do not have data to derive the exact trajectory towards the global equilibrium, we observe both analytically and by simulations how an highly heterogeneous network, such as SF [39], allow the cooperation to emerge in the social multiplex network. Furthermore, high homophily values lead more quickly to local Nash equilibria and then the global Nash equilibrium, by speeding up the formation of groups of cooperators, increasing their size and enhancing the network resilience against an invasion of defectors [11].

Fig. 5 shows how the density $\alpha$ of Nash pairs varies over the time, considering high homophily values and a SF as network substrate. We can observe phase transitions with the emergence of local metastable Nash equilibria, and finally the global Nash equilibrium given by the overall cooperation.
4.5. User Reputation Score in a MCS scenario

We have simulated a simple scenario of vehicular crowdsensing applications (services) using synthetic generated following an approach similar to that in [1]. We have considered synthetic data of a simple scenario of a vehicular crowdsensing application, but our modeling approach is generic and may be extended to any kind of MCS service. We formulate the MCS in vehicular networks and the interactions between human users/vehicles equipped with sensors as a vehicular crowdsensing game. Each of them participates to the sensing task and chooses its strategy based on some constraints related to sensing costs/risks and gains derived from the accomplishment of the sensing task. As discussed earlier, we consider both the quantity (degree of participation) and quality (accuracy of contributions) of the reported events [15, 1]. They represent the contributors’ profiles and have been used as input data. Then, following the proposed game-theoretic modeling approach, we have measured the user reputation scores for each human node in the different configurations of network structure and social dilemmas. By looking at Fig. 6, we can observe how in the SF case, user reputation scores assume high values distributed between 0.85 and 1.0, significantly higher than in the ER and SW cases. Indeed, in the ER and SW cases scores are mainly distributed in the range between 0 and 0.4. We can also observe how the SW network behaves worse than ER in terms of user reputation scores.

5. Conclusions

In MCS application scenarios, based on participatory sensing, human behaviours assume increasingly a crucial role in the operational reliability of the MCS services. Incentive mechanisms are therefore designed to motivate users to contribute focusing both on the quality and quantity of contributions [1]. In this work, we have proposed a methodology which represents the core of a Decision Support System (DSS) for designing incentive mechanisms, extracting the rules and human-centric policies or metrics to disburse incentives to human users. Other than simultaneously participate to various services, they are social nodes that interact each other on a weighted social multiplex network, where each layer corresponds to a distinct type of relation among them and weight of each connection depends on homophily between nodes. We have analysed such interactions and quantified the role of homophily, network heterogeneity and multiple interactions in shaping human sensing behaviours on a networked scenario. We have therefore defined a game-theoretic modeling approach which allows us to get a multi-scale integration of all these issues, quantifying the emergence and resilience of cooperation on the weighted social multiplex network. In this way, it has been possible to detect which configurations of both social dilemmas and network structure bring out the emergence and sustainability of cooperation. Then, by considering a simple scenario of MCS and synthetic data related to a vehicular crowdsensing scenario as input data of our model, we have measured the user reputation scores in a synthetic social multiplex network, based on the configurations detected in the previous evolutionary dynamics. Findings have confirmed how user reputation scores are higher for those configurations more able to make cooperation emerge and sustain in the network. We have therefore
Figure 6: **User Reputation scores.** The figure shows the user reputation scores (y-axis) against nodes (x-axis) (a) in two configurations of network structure and social dilemmas, and (b) a comparison between the user reputation scores deriving from different network structures considering the same social dilemma (PD) (see Text).
Figure 7: Game-theoretic modeling for designing incentive mechanisms in MCS. The figure shows a conceptual description of the proposed methodology, which has been also implemented in the software. Starting from the dynamic patterns of connectivity on a multi-layer social sensing framework, which includes homophily, network heterogeneity (network structures in the block correspond to ER, SF and SW networks), the game-theoretic modeling leads us to quantify the truthfulness measures, and define the core of a DSS for designing incentive mechanisms.

proposed to include also social dynamics, multiplexity and human-related issues in the design of socially-aware and human-centric incentive mechanisms.

In Fig. 7 we conceptually map the various aspects of the proposed methodology onto the MCS space. Starting from the dynamic patterns of connectivity, the multi-layer social sensing framework, which includes homophily, network heterogeneity and multiplex structure measures, and the game-theoretic modeling guides choices according to human sensing behaviours. It leads to evaluate and quantify the human-centric policies, defining a MCS space that allows us to quantify the truthfulness measures for designing incentive mechanisms. We therefore get a Decision Support System (DSS) able to perform a decision making process related to disbursing incentives to users based on dynamic and human-centric policies. As in [40], these policies represent a minimised set of rules extracted from both qualitative and quantitative information and data related to human users and their behaviours. Thus, the DSS results from the analysis and quantification through a game-theoretic modeling approach which allows us to join and combine multiplexity, network heterogeneity and human-related factors represented by homophily.

We envisage that the proposed methodology, enclosing social dynamics, multiplexity and human-related issues, may provide new insights in the future design of socially-aware and human-centric incentive mechanisms. Furthermore, in the future work, the idea is to include a dynamic definition of weights and payoffs related to micro-packets of energy exchanged between nodes, i.e., micro-
affirmations and micro-inequities [34], to better understand the evolutionary dynamics of the human sensing behaviours. Moreover, we aim at further validating the efficacy of the proposed methodological approach by exploiting real data sets of various MCS scenarios, also including other environmental, social and behavioural MCS applications.

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