Interactive Sensing and Decision Making in Social Networks

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Contents

Abstract

The proliferation of social media such as real time microblogging and online reputation systems facilitate real time sensing of social patterns and behavior. In the last decade, sensing and decision making in social networks have witnessed significant progress in the electrical engineering, computer science, economics, finance, and sociology research communities. Research in this area involves the interaction of dynamic random graphs, socio-economic analysis, and statistical inference algorithms. This monograph provides a survey, tutorial development, and discussion of four highly stylized examples: social learning for interactive sensing; tracking the degree distribution of social networks; sensing and information diffusion; and coordination of decision making via game-theoretic learning. Each of the four examples is motivated by practical examples, and comprises of a literature survey together with careful problem formulation and mathematical analysis. Despite being highly stylized, these examples provide a rich variety of models, algorithms and analysis tools that are readily accessible to a signal processing, control/systems theory, and applied mathematics audience.

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Introduction and Motivation

Research in social networks involves the interplay of complex networks (dynamics of random graphs) and social analysis (stemming from the areas of economics and sociology). There are seminal books in this area including [132, 249]. In comparison, this monograph deals with *sensing and decision-making* in social networks. The proliferation of social media such as real-time microblogging services (Twitter[1]), online reputation and rating systems (Yelp) together with app-enabled smartphones, facilitate real time sensing of social activities, social patterns, and behavior.

Sensing and decision making in social networks is an area that has witnessed remarkable progress in the last decade in electrical engineering, computer science, economics, finance, and sociology. It is the aim of this monograph to survey some important topics in this area and present highly stylized examples that are readily accessible to a signal processing, control/systems theory, and applied mathematics audience. Indeed, the main tools used in this monograph are dynamic programming, Bayesian estimation (filtering), stochastic approximation (adaptive filtering) and their convergence analysis (weak convergence and mean square analysis), game-theoretic learning, and

[1]On US Presidential election day in 2012, there were 15 thousand tweets per second resulting in 500 million tweets in the day. Twitter can be considered as a real-time sensor.

graph theory. There has been much recent activity in the signal processing community in the area of social networks. "How global behavior emerges from simple local behavior of boundedly rational agents" has been an underlying theme of an NSF/UCLA workshop in 2010, special sessions at ICASSP 2011 and 2012 and the ICASSP 2011 expert summary in [270]. Also, the recent special issues [227, 268] deal with signal processing of social networks.

1.1 Motivation

Social sensing [5, 41, 44, 75] is defined as a process where physical sensors present in mobile devices such as GPS are used to infer social relationships and human activities. In this monograph, we work at a higher level of abstraction. We use the term *social sensor* or *human-based sensor* to denote an agent that provides information about its environment (state of nature) on a social network after interaction with other agents. Examples of such social sensors include Twitter posts, Facebook status updates, and ratings on online reputation systems like Yelp and Tripadvisor. Such social sensors go beyond physical sensors for social sensing [221]. For example, user opinions/ratings (such as the quality of a restaurant) are available on Tripadvisor but are difficult to measure via physical sensors. Similarly, future situations revealed by the Facebook status of a user are impossible to predict using physical sensors.

Statistical inference using social sensors is relevant in a variety of applications including localizing special events for targeted advertising [59, 171], marketing [245], localization of natural disasters [222], and predicting sentiment of investors in financial markets [33, 208]. It is demonstrated in [13] that models built from the rate of tweets for particular products can outperform market-based predictors. However, social sensors present unique challenges from a statistical estimation point of view. First, social sensors interact with and influence other social sensors. For example, ratings posted on online reputation systems strongly influence the behaviour of individuals[2]. Such interactive sensing can result in non-standard information patterns due to correlations introduced by the structure of the underlying social network. Second, due to privacy reasons and time constraints, social sensors typically

[2]It is reported in [130] that 81% of hotel managers regularly check Tripadvisor reviews. It is reported in [187] that a one-star increase in the Yelp rating maps to 5-9 % revenue increase.

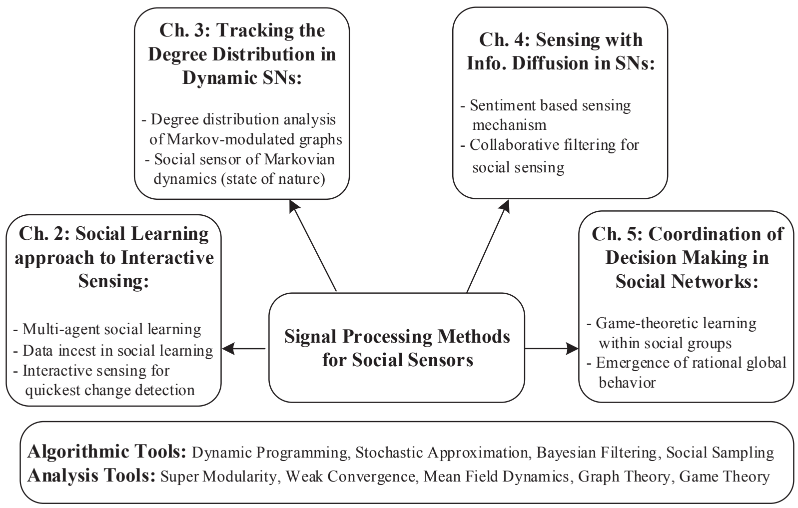

Figure 1.1: Main results and organization of the monograph.

do not reveal raw observations of the underlying state of nature. Instead, they reveal their decisions (ratings, recommendations, votes) which can be viewed as a low resolution (quantized) function of their raw measurements and interactions with other social sensors.

As is apparent from the above discussion, there is strong motivation to construct mathematical models that capture the dynamics of interactive sensing involving social sensors. Such models facilitate understanding the dynamics of information flow in social networks and, therefore, the design of algorithms that can exploit these dynamics to estimate the underlying state of nature. In this monograph, *social learning* [23, 31, 50], *game-theoretic learning* [92, 121], and *stochastic approximation* [167, 263] serve as useful mathematical abstractions for modelling the interaction of social sensors.

1.2 Main Results and Organization

As can be seen from Figure 1.1, this monograph is organized into four chapters (excluding this introductory chapter) that provide a survey, tutorial development, and discussion of four highly stylized examples: social learning for interactive sensing; tracking the degree distribution of social networks; sensing and information diffusion; and coordination of decision-making via game-theoretic learning. Each of the four chapters is motivated by practical examples, and comprises of a literature survey together with careful problem formulation and mathematical analysis. The examples and associated analysis are readily accessible to a signal processing, control/systems theory, and applied mathematics audience.

In terms of information patterns, Chapter 2 considers Bayesian estimation and sequential decision making with sequential information flow and then information flow over small directed acyclic graphs. In comparison, Chapter 3 considers stochastic approximation algorithms for large random graphs that evolve with time. Chapter 4 considers the asymptotics of large graphs with fixed degree distribution but where the state of individual node in the graph evolve over time—this models information diffusion. The mean field analysis in Chapter 4 results in a stochastic approximation type recursion, and the estimation problems are Bayesian (nonlinear filtering). Finally, Chapter 5 deals with learning in non-cooperative repeated games comprising networks of arbitrary size—the algorithms are of the stochastic approximation type. In all these cases, sensors interact with and influence other sensors. It is the understanding of this interaction of local and global behaviors in the context of social networks that constitutes the unifying theme of this monograph.

Below we give a brief synopsis of these four chapters.

1. Social Learning Approach to Interactive Sensing

Chapter 2 presents models and algorithms for interactive sensing in social networks where individuals act as sensors and the information exchange between individuals is exploited to optimize sensing. Social learning is used as a mathematical formalism to model the interaction between individuals that aim to estimate an underlying state of nature.

Social learning in multi-agent systems seeks to answer the following question:

> *How do decisions made by agents affect decisions made by subsequent agents?*

In social learning, each agent chooses its action by optimizing its local utility function. Subsequent agents then use their private observations together with the decisions of previous agents to estimate (learn) the underlying state of nature. The setup is fundamentally different to classical signal processing in which sensors use noisy observations to compute estimates.

In the last decade, social learning has been used widely in economics, marketing, political science, and sociology to model the behavior of financial markets, crowds, social groups, and social networks; see [1, 2, 23, 31, 50, 180] and numerous references therein. Related models have been studied in the context of sequential decision making in information theory [65, 126] and statistical signal processing [51, 162] in the electrical engineering literature.

Social learning models for interactive sensing can predict unusual behavior. Indeed, a key result in social learning of an underlying random variable is that rational agents eventually herd [31]; that is, they eventually end up choosing the same action irrespective of their private observations. As a result, the actions contain no information about the private observations and so the Bayesian estimate of the underlying random variable freezes. For a multi-agent sensing system, such behavior can be undesirable, particularly if individuals herd and make incorrect decisions.

In this context, the following questions are addressed in Chapter 2: How can self-interested agents that interact via social learning achieve a trade-off between individual privacy and reputation of the social group? How can protocols be designed to prevent data incest in online reputation blogs where individuals make recommendations? How can sensing by individuals that interact with each other be used by a global decision maker to detect changes in the underlying state of nature? Chapter 2 presents an overview, insights and discussion of social learning models in the context of data incest propagation, change detection, and coordination of decision making.

Several examples in social networks motivate Chapter 2. Design of protocols to prevent data incest are motivated by the design of fair online reputation systems such as Yelp or Tripadvisor. In Online reputation systems, which maintain logs of votes (actions) by agents, social learning takes place with information exchange over a loopy graph (where the agents form the vertices of the graph). Due to the loops in the information exchange graph, *data incest* (misinformation) can propagate: Suppose an agent wrote a poor rating of a restaurant on a social media site. Another agent is influenced by this rating, visits the restaurant, and then also gives a poor rating on the social media site. The first agent visits the social media site and notices that another agent has also given the restaurant a poor rating—this double confirms her rating and she enters another poor rating. In a fair reputation system, such "double counting" or data incest should have been prevented by making the first agent aware that the rating of the second agent was influenced by her own rating.

As an example of change detection, consider measurement of the adoption of a new product using a micro-blogging platform like Twitter. The adoption of the technology diffuses through the market but its effects can only be observed through the tweets of select members of the population. These selected members act as sensors for the parameter of interest. Suppose the state of nature suddenly changes due to a sudden market shock or presence of a new competitor. Based on the local actions of the multi-agent system that is performing social learning, a global decision maker (such as a market monitor or technology manufacturer) needs to decide whether or not to declare if a change has occurred. How can the global decision maker achieve such change detection to minimize a cost function comprised of false alarm rate and delay penalty? The local and global decision makers interact, since the local decisions determine the posterior distribution of subsequent agents which determines the global decision (stop or continue) which determines subsequent local decisions.

2. Tracking Degree Distribution of Social Networks

Chapter 3 considers dynamical random graphs. The degree of a node in a network (also known as the connectivity) is the number of connections the node has in that network. The most important measure that characterizes the structure of a network (specially when the size of the network is large and the connections—adjacency matrix of the underlying graph—are not given) is the *degree distribution* of the network. Chapter 3 considers a Markov-modulated duplication-deletion random graph where, at each time instant, one node can either join or leave the network with probabilities that evolve according to the realization of a finite state Markov chain (state of nature). This chapter deals with the following questions:

> *How can one estimate the state of nature using noisy observations of nodes' degrees in a social network?* and *How good are these estimates?*

Chapter 3 comprises of two results. First, motivated by social network applications, we analyze the asymptotic behavior of the degree distribution of the Markov-modulated random graph. From this degree distribution analysis, we can study the connectivity of the network, the size and the existence of a large connected component, the delay in searching such graphs, etc. [86, 132, 204, 202]. Second, a stochastic approximation algorithm is presented to track the empirical degree distribution as it evolves over time. We further show that the stationary degree distribution of Markov-modulated duplication-deletion random graphs depends on the dynamics of such graphs and, thus, on the state of nature. This means that, by tracking the empirical degree distribution, the social network can be viewed as a social sensor to track the state of nature. The tracking performance of the algorithm is analyzed in terms of mean square error. A functional central limit theorem is further presented for the asymptotic tracking error.

An important associated problem discussed in Chapter 3 is how to actually construct random graphs via simulation algorithms. In particular, for large social networks, only the degree sequence is available, and not the adjacency matrix. (The degree sequence is a non-increasing sequence of vertex degrees.) Does a simple graph exist that realizes a particular degree sequence? How can all graphs that realize a degree sequence be constructed? Chapter 3 presents a discussion of these issues.

3. Sensing and Information Diffusion in Social Networks

Chapter 4 considers the following questions:

> *How does a behavior diffuse over a social network comprising of a population of interacting agents?* and *How can an underlying stochastic state be estimated based on sampling the population?*

As described in [184], there is a wide range of social phenomena such as diffusion of technological innovations, cultural fads, and economic conventions [50], where individual decisions are influenced by the decisions of others. Chapter 4 considers two extensions of the widely used Susceptible-Infected-Susceptible (SIS) models for diffusion of information in social networks [183, 184, 132, 212, 249]. First, the states of individual nodes evolve over time as a probabilistic function of the states of their neighbors *and* an underlying target process. The underlying target process can be viewed as the market conditions or competing technologies that evolve with time and affect the information diffusion. Second, the nodes in the social network are sampled randomly to determine their state. Chapter 4 reviews recent methods for sampling social networks such as social sampling and respondent-driven sampling. As the adoption of the new technology diffuses through the network, its effect is observed via sentiment (such as tweets) of these selected members of the population. These selected nodes act as social sensors. In signal processing terms, the underlying target process can be viewed as a signal, and the social network can be viewed as a sensor. The key difference compared to classical signal processing is that the social network (sensor) has dynamics due to the information diffusion. Our aim is to estimate the underlying target state and the state probabilities of the nodes by sampling measurements at nodes in the social network. In a Bayesian estimation context, this is equivalent to a filtering problem involving estimation of the state of a prohibitively large-scale Markov chain in noise. The key idea is to use *mean field dynamics* as an approximation (with provable bounds) for the information diffusion and, thereby, obtain a tractable model.

4. Coordination of Decisions as Non-cooperative Game-Theoretic Learning

Chapter 5 studies game-theoretic learning in the context of social networks. Game theory has traditionally been used in economics and social sciences with a focus on fully rational interactions where strong assumptions are made on the information patterns available to individual agents. In comparison, social sensors are agents with partial information and it is the dynamic interactions among such agents that is of interest. This, together with the interdependence of agents' choices, motivates the need for game-theoretic learning models for agents interacting in social networks.

Chapter 5 deals with the question:

When individuals are self-interested and possess limited sensing

> *and communication capabilities, can a network of such individuals achieve sophisticated global behavior?*

We discuss a non-cooperative game-theoretic learning approach for adaptive decision making in social networks. This can be viewed as non-Bayesian social learning. The aim is to ensure that all agents eventually choose actions from a common polytope of randomized strategies—namely, the set of correlated equilibria [18, 20] of a non-cooperative game. The game-theoretic concept of equilibrium describes a condition of global coordination where all decision makers are content with the social welfare realized as the consequence of their chosen strategies.

We consider two examples of information exchange among individuals. The first example comprises of fully social agents that can communicate with every other agent in the network. This provides a simple framework to present the "regret-matching" [117, 121] decision making procedure that ensures convergence of the global behavior of the network to the correlated equilibria set. In the second example, we confine the information flow to social groups—each individual can only speak with her neighbors. Accordingly, the regret-matching procedure is revised to adapt to this more practical social network model. Finally, we consider the case of homogeneous social groups, where individuals share and are aware of sharing the same incentives. The regret-matching procedures is then adapted to exploit this valuable piece of information available to individuals within each social group. The final result in this chapter considers the scenario where the non-cooperative game model evolves with time according to the sample path of a finite-state Markov chain. It is shown that, if the speed of the Markovian jumps and the learning rate of the regret-matching algorithm match, the global behavior emerging from a network of individuals following the presented algorithms properly tracks the time-varying set of correlated equilibria.

One of the main ideas in this chapter is that the limit system that represents the game-theoretic learning algorithms constitutes a differential inclusion. Differential inclusions are generalization of ordinary differential equations (ODEs)[3], and arise naturally in game-theoretic learning, since the strate-

[3] A generic differential inclusion is of the form $dX/dt \in \mathcal{F}(X,t)$, where $\mathcal{F}(X,t)$ specifies a family of trajectories rather than a single trajectory as in the ordinary differential equations $dX/dt = F(X,t)$. See §5.4.3 and Appendix B for more details.

gies according to which others play are unknown. This is highly non-standard in the analysis of stochastic approximation algorithms in which the limit system is usually an ODE.

Chapter 5 ends with an example that shows how the presented algorithms can be applied in a social sensing application. We consider the problem of estimating the true value of an unknown parameter via a network of sensors. There have been a lot of recent works that study diffusion of information over graphs linking a multitude of agents; see [226, 225] and numerous references therein. We particulary focus on diffusion least mean square (LMS) algorithms [182]: each sensor decides whether to activate, and if activates, (i) it will exchange estimate with neighbors and fuse the collected data; (ii) it will use the fused data and local measurements to refine its estimate via an LMS-type adaptive filter. Using a game-theoretic formulation, an energy-aware activation mechanism is devised that, taking into account the spatial-temporal correlation of sensors' measurements, prescribes sensors when to activate. We first show that, as the step-size in the diffusion LMS approaches zero, the analysis falls under the unifying classical stochastic approximation theme of this chapter and, therefore, can be done using the well-known ODE method [167]. It is then shown that the proposed algorithm ensures the estimate at each sensor converges to the true parameter, yet the global activation behavior along the way tracks the set of correlated equilibria of the underlying activation control game.

5. Appendices

The two appendices at the end of this monograph present, respectively, a mean-square error analysis and weak convergence analysis of two different types of stochastic approximation algorithms used to track time-varying behavior in social networks. These analysis are crucial in allowing us to predict the asymptotic dynamics of such algorithms. The chapters provide sufficient intuition behind the theorems and the reader can skip the appendices without loss of continuity. Appendix A generalizes the asymptotic analysis of duplication deletion random graphs in [61] to the case of Markov-modulated graphs. It uses the concept of perturbed Lyapunov functions. The weak convergence analysis presented in Appendix B generalizes the convergence analysis provided in the seminal papers [117, 119] to the case where the game-theoretic learning algorithm can track a time-varying correlated equilibrium. The convergence analysis in both appendices are presented in a tutorial fashion and are readily accessible to researchers in adaptive filtering, stochastic optimization, and game theory.

Out-of-Scope Topics

Other important problems that have been extensively studied in the literature, but are outside the scope of this monograph include: consensus formation [132, Chapter 8], [149, 240], metrics for measuring networks (other than degree distribution) [132, Chapter 2], [253], small world [144, 254, 255], cooperative models of network formation [131, Chapter 1], [132, Chapter 12], [233], behavior dynamics in peer-to-peer media-sharing social networks [112, 267], and privacy and security modeling [169, 179]. The interested reader is referred to the above cited works and references therein for extensive treatment of the topics.

1.3 Perspective

The social learning and game-theoretic learning formalisms considered in this monograph can be used either as descriptive tools, to predict the outcome of complex interactions amongst agents in sensing, or as prescriptive tools, to design social networks and sensing systems around given interaction rules. Information aggregation, misinformation propagation and privacy are important issues in sensing using social sensors. In this monograph, we treat these issues in a highly stylized manner so as to provide easy accessibility to an electrical engineering audience. The underlying tools used in this monograph are widely used by the electrical engineering research community in the areas of signal processing, control, information theory and network communications. The fundamental theory of network science is well-documented in seminal books such as [76, 132] and involves the interplay of random graphs and game theory.

In Bayesian estimation, the twin effects of social learning (information aggregation with interaction amongst agents) and data incest (misinformation propagation) lead to non-standard information patterns in estimating the underlying state of nature. Herding occurs when the public belief overrides the private observations and, thus, actions of agents are independent of their private observations. Data incest results in bias in the public belief as a consequence of the unintentional re-use of identical actions in the formation of public belief in social learning—the information gathered by each agent is mistakenly considered to be independent. This results in overconfidence and bias in estimates of the state of nature.

Tracking a time-varying parameter that evolves according to a finite-state Markov chain (state of nature) is a problem of much interest in signal processing [30, 87, 259]. In social networks, sometimes the parameter under study (state of nature) cannot be sensed by pervasive sensors, e.g., the level of happiness in a community, the tendency of individuals to expand their networks, the strength of social links between individuals, etc. In such cases, social sensors can do much better than pervasive sensors. A social network with a large number of individuals can be viewed as an interactive sensing tool to obtain information about individuals or state of nature; this is a social sensor. Motivated by social network applications, a social sensor based framework is presented in Chapter 3 to track the degree distribution of Markov-modulated dynamic networks whose dynamics evolve over time according to a finite-state Markov chain.

Privacy issues impose important constraints on social sensors. Typically, individuals are not willing to disclose private observations. Optimizing interactive sensing with privacy constraints is an important problem. Privacy and trust pose conflicting requirements on human-based sensing: Privacy requirements result in noisier measurements or lower resolution actions, while maintaining a high degree of trust (reputation) requires accurate measurements. Utility functions, noisy private measurements, and quantized actions are essential ingredients of the social and game-theoretic learning models presented in this monograph that facilitate modelling this trade-off between reputation and privacy.

In social sensor systems, the behavior is driven by the actions of a large number of autonomous individuals, who are usually self-interested and optimize their respective objectives. Often, these individuals form social contacts (i.e. links) by choice, rather than by chance. Further, there are always social and economic incentives associated with forming such social contacts based on the information obtained about the state of the nature or contribution to the diffusion of information across the network. The social network analysis using the common graph-theoretic techniques, however, fails to capture the behavior of such self-interested individuals and the dynamics of their interaction. This motivates the use of game-theoretic methods. Game-theoretic learning explains how coordination in the decisions of such self-interested individuals might arise as a consequence of a long-run process of adaptation and learning in an interactive environment [94]. Interestingly enough, while each individual has limitations in sensing and communication, the coordinated behavior amongst individuals can lead to the manifestation of sophisticated behavior at the network level.

The literature in the areas of social learning, sensing, and networking is extensive. In each of the following chapters, we provide a brief review of relevant works together with references to experimental data. The book [50] contains a complete treatment of social learning models with several remarkable insights. For further references, we refer the reader to [151, 153, 154, 161, 191]. In [116], a nice description is given of how, if individual agents deploy simple heuristics, the global system behavior can achieve "rational" behavior. The related problem of achieving *coherence* (i.e., agents eventually choosing the same action or the same decision policy) among disparate sensors of decision agents without cooperation has also witnessed intense research; see [215] and [251]. Non-Bayesian social learning models are also studied in [79, 80].

There is also a growing literature dealing with the interplay of technological networks and social networks [55]. For example, social networks overlaid on technological networks account for a significant fraction of Internet use. Indeed, as discussed in [55], three key aspects of that cut across social and technological networks are the emergence of global coordination through local actions, resource sharing models and the wisdom of crowds (diversity and efficiency gains). These themes are addressed in the current paper in the context of social learning.

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