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INFORMATION COMMUNITIES IN SOCIAL NETWORKS. PART I: FROM CONCEPT TO MATHEMATICAL MODELS[1]

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Abstract. This survey covers the literature related to information communities in mutually complementary areas: the formation of information communities in social networks and some applied aspects of identifying and analyzing information communities in social networks. First, mathematical models describing the formation of information communities under uncertainty are considered. Among these models, the most relevant ones are the mathematical models of opinion/belief dynamics reflecting any changes in the beliefs of nodes under the influence of other network nodes and significant effects (in particular, the preservation of differences in beliefs and the divergence of beliefs) that lead to the formation of information communities. In part I of the survey, the concept of an information community is first presented. Then information processing and decision-making by an agent in a social network under external uncertainty are outlined. The factors influencing the formation of information communities in the network are highlighted, and the basic models of Bayesian agents and their extensions are investigated.

Keywords: social networks, information community, formation of information communities, analysis of information communities, belief formation.

INTRODUCTION

The Internet and online social networks have opened up great opportunities for the efficient production, distribution, and consumption of information in society and, therefore, opportunities for rational discussion of various issues and the formation of balanced opinions on them. However, as it turned out, the availability and diversity of information sources and the corresponding alternative points of view do not automatically improve the quality of the information received and the competence of people in socially important issues. On the contrary, the ideas on many issues in society diverge, and separate communities are formed with different or even exact antipodes of opinions on the same issues. This phenomenon can be explained as follows: social network participants are not completely rational agents effectively aggregating information on issues of interest to them since social and psychological factors significantly influence the processing of information by individuals.

In many application areas, an important problem is identifying and studying *information communities* in social networks (the sets of individuals with similar and stable ideas on a certain issue). For example, social and political scientists believe that the formation of isolated communities (information bubbles and echo chambers) poses a threat to society. Empirical research shows a rich variety of information communities in society (for example, polarized communities of Republicans and Democrats in the United States). In such studies, various aspects were analyzed: the exposure of a user to alternative information depending on the preferences of his contacts in the network and online social network algorithms [1], the interaction of communities with different beliefs [2], the informational roles of users [3], etc. Statistical methods, machine learning methods (for example, correlation and cluster

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analysis methods), and social network analysis methods based on the phenomenon of homophily[2] are often used [1–5]. Such methods require preliminary data processing and subsequent interpretation of the results. In other words, a researcher must have an idea of the opinion dynamics in social networks and the existence of information communities in them. Features of information processing by an individual are explored in cognitive science, psychology, and social psychology; for example, see the book [8]. Formal microlevel models of boundedly rational agents are developed to describe the belief dynamics in networks taking these features into account. For example, we refer to [9–13]. In practice, applying these models to identify communities is not easy due to the simplifications and assumptions accepted, the complexity of identifying the model parameters, and the absence of a clearly formulated concept of information communities.

This survey aims to consider the formation models of information communities in social networks (which have microeconomic, cognitive, or socio-psychological foundations) and methods for their identification. The survey is divided into three parts, and part I has the following structure. In Section 1, we define an information community. In Section 2, we briefly describe the process of information processing and decision-making by an agent in a social network under an external uncertainty; also, we highlight the factors affecting the belief dynamics in a social network and, consequently, the formation of information communities in the network. In Section 3, we briefly discuss formal models of the belief dynamics with Bayesian agents leading to the formation of information communities.

1. CONCEPT OF INFORMATION COMMUNITY

Community is a rather vague concept often used informally. Here are some of the definitions available. Community is "an association of humans, peoples, or states with common interests or goals" [14]. A community can be viewed:

• as an association of individuals, i.e.,

– as a group of people with common characteristics or interests, living together within a larger society,

– as a set of individuals with common interests, distributed throughout society,

– as an association of people or nations with a common history or common social, economic, and political interests;

• as a society as a whole [15].

Examples are scientific communities and language communities.

According to these definitions, the characteristics of all individuals within a community are common. This effect is closely related to *homophily*, the inclination of individuals to form relations based on common characteristics [6, 7]. From this point of view, there is a direct connection with the definition adopted in the theory of complex networks, where a community is a set of nodes connected with each other rather than with the nodes of other communities [16]. As such characteristics, we will be concerned with the beliefs of individuals (private beliefs) about some issues (problems). Therefore, we will understand the information *community* as a set of individuals—social network members—united by common stable beliefs[3] about given issues; see the formal definition of a community introduced in the paper [17].

For describing and explaining the formation dynamics of information communities in social networks, appropriate models of the dynamics of private beliefs are needed. Let us distinguish between two types of significant dynamic processes in social networks (Fig. 1): the process of changing the beliefs of network individuals (the network state) within a fixed topology and the process of changing the network topology when the network state "affects" the topology (like-minded people begin to interact more with each other). It is usually assumed that the topology dynamics occur in slow time, whereas the state dynamics in fast time. The most interesting and complex situations are when both processes influence each other, thereby affecting the formation of information communities in a social network.

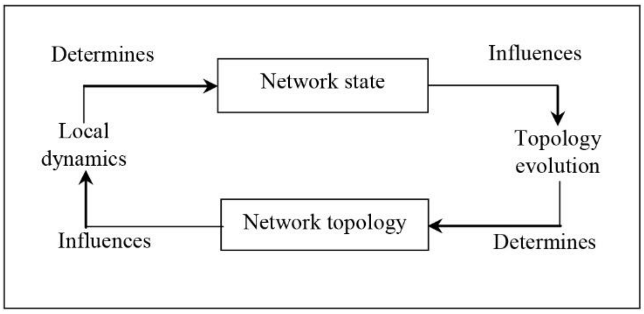

Fig. 1. Mutual influence of network state and topology.

[2] Homophily is actively studied in sociology. In particular, the evidence of and reasons for this phenomenon are considered; for example, see [6, 7]. This paper does not cover the results obtained in sociology.

[3] The terms "belief" and "opinion" are considered synonyms.

This survey considers dynamic models of beliefs in networks with a fixed structure (in some cases, with changing weights of links), where individuals try to eliminate the uncertainty regarding a given issue via social interactions. The common final beliefs of individuals are the condition for forming information communities in the network. These models are discussed further in parts I and II of the survey.

2. FORMING BELIEFS IN SOCIAL NETWORK

Participants of social networks exchange information to eliminate the uncertainty on some issue, forming their beliefs. (In mathematical models, issues are usually formalized by the values of some parameters.) In control of socio-economic systems, a common assumption is that rational individuals (agents) have beliefs about the state of the world $\theta \in \Theta$ (also called the state of nature). The agent's individual preferences are defined on the set of activity results, which particularly depend on the agent's actions and the state of the world. Under the hypothesis of rational behavior, each agent chooses an action yielding the best result for him. The information he possesses regarding the state of the world is essential here. A rational agent seeks to eliminate the existing uncertainty and make decisions under complete information (the hypothesis of determinism) [18]. This paper primarily considers the elimination of an external objective uncertainty (the uncertain state of the world). It is assumed that a rational formation about the state of the world while interacting with his neighbors (whose actions reveal their private information), changing his beliefs according to some updating mechanisms (or information processing rules); see Fig. 2. Rational agents calculate their posterior beliefs by Bayes' rule.

However, individuals are not completely rational. As noted by psychologists [19–21], individuals have *bounded rationality* due to various cognitive limitations (primarily, limited memory and limited computational capabilities) and mental characteristics; see mental components in Fig. 2 and their detailed description in [22]. Moreover, individuals make systematic errors that affect information processing (cognitive biases). Therefore, heuristic updating methods can be considered here, which are based on empirical laws and demonstrate the socio-psychological effects observed in practice. In particular, the social influence on the private beliefs was described in the classical DeGroot model [9]: an agent updates his belief based on the information about the beliefs of his trusted environment in a social network. In meaningfully richer models (for example, those presented in [10–12]), the strength of the influence of neighbors depends on how much their beliefs agree with the agent's belief: the individual's inclination to confirm his point of view is taken into account. This effect can lead to the emergence of communities in which the agents support the same beliefs.

Generally speaking, the dynamics of private beliefs in a social network are influenced by the following factors (Fig. 2):

- *The state of the world* $\theta \in \Theta$ regarding which individuals form their beliefs (for example, the shape of the Earth or a currency exchange rate for tomorrow).
- *The individual's belief about the state of the world*. The belief can be defined, in particular, using some point estimate or distribution of subjective probabilities on the set Θ. The individual's beliefs are limited by memory and may depend on his beliefs about other issues.
- *The updating mechanism for beliefs*. Control of socio-economic systems rests on the assumption that the agents are rational and act according to Bayes' rule. However, boundedly rational individuals can apply heuristic rules.
- *The individual's action*, which reflects his beliefs. Actions from discrete sets are usually less informative than those from continuous ones due to an insufficiently good reflection of the agent's beliefs.
- *The individual's preferences*, defined on the set of his activity results, or a preferences-induced objective function that depends on the individuals' actions and the state of the world.
- *The social network structure*. Obviously, the network structure influences the formation of the private beliefs. Here are some examples of network effects: disconnected networks rarely lead to the coordinated beliefs of individuals; individuals with an advantageous position in the network structure usually have a significant impact on the opinions of others, etc.

Each of these factors concerns the mental characteristics of individuals and determines various information effects in a social network. The models of belief dynamics describe the following information effects:

– *the emergence of a true or false consensus of beliefs in the network* and, consequently, the formation of a global information community (see the definitions in Section 1);

– *the emergence of some disagreement in the network* and, consequently, the formation of various information communities in the network.

The mathematical models of belief dynamics for network agents (see below) incorporate the factors listed above and demonstrate these information effects and, therefore, the possibility of forming information communities in the network. A primary approach is to divide the models, according to the intellectual capabilities of network agents and the updating method for their beliefs, into the models with rational Bayesian agents and the models with boundedly rational agents guided by heuristic belief updating rules.

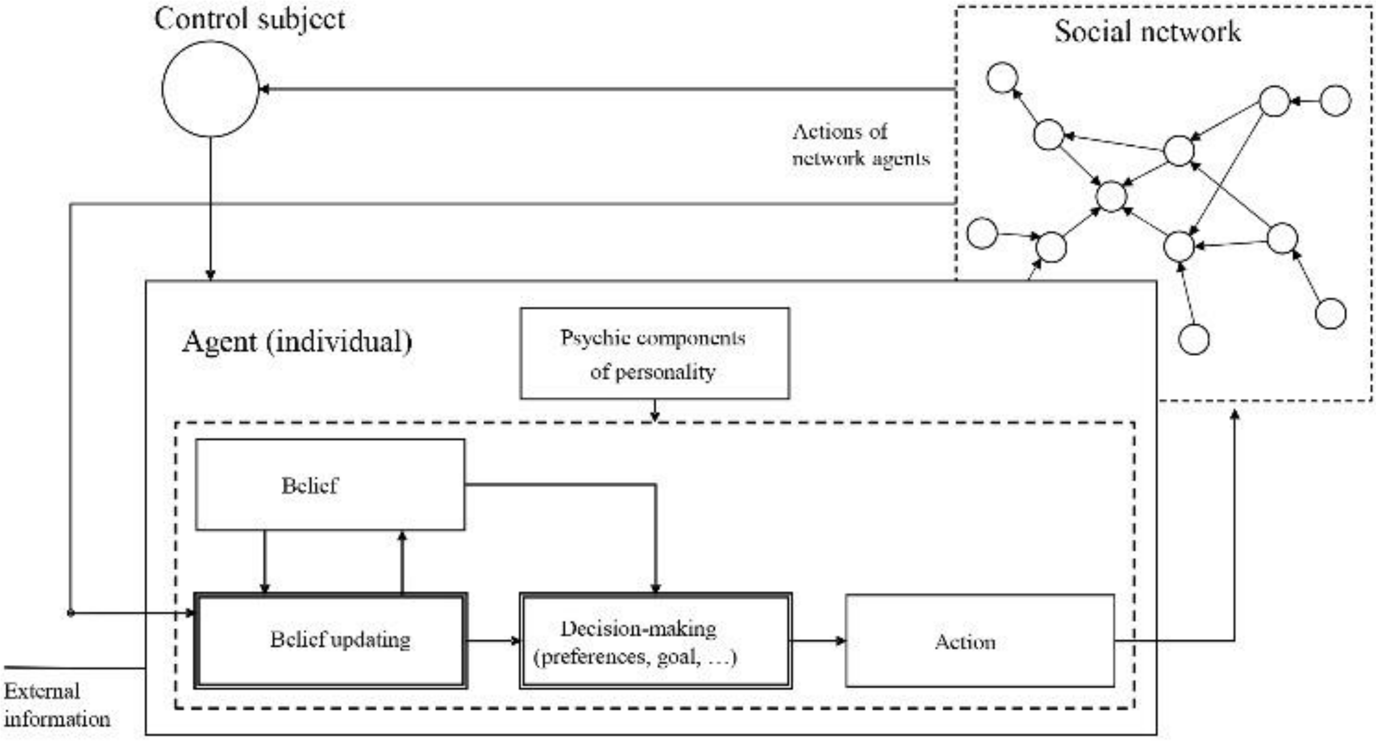

Fig. 2. Information processing and decision-making by agent in social network.

3. FORMING INFORMATION COMMUNITIES IN MODELS WITH BAYESIAN AGENTS

3.1. Forming Private Beliefs

In models with Bayesian agents, the main question is whether the agents can form true beliefs about the state of the world in a network. For the state of the world, the set of admissible values Θ is given, like the set of agents having probability distribution-based beliefs about the state of the world. The agent's learning occurs by processing his available information about the state of the world: *a private signal* and, possibly, the actions of his neighbors. In the latter case (the agent receives information about the actions of his neighbors), learning is called social. For being informative, a signal s must depend on the state of the world θ. However, generally speaking, it does not completely reveal the state of the world, representing a random variable. Information processing obeys Bayes' rule: the incoming information is used to update the individual's prior beliefs and form his posterior beliefs:

$$f(\theta|s) = \frac{\phi(s\,|\,\theta)\, f(\theta)}{\int \phi(s|\theta)\, f(\theta)\, d\theta},$$

where $f(\theta)$ denotes the prior density function of θ; $\phi(s|\theta)$ and $f(\theta|s)$ are the conditional density functions of the parameters s and θ given θ and s, respectively.

In classical learning models, all agents know the model structure: the prior probabilities of the admissible states of nature and the private signals (their conditional distributions given different states of nature). This information is *common knowledge*:

1) Each agent knows this structure.

2) All agents know fact 1);

3) All agents know fact 2), and so on, ad infinitum.

However, each agent knows neither the realizations of the state of the world nor the realizations of the other agents' private signals. The common knowledge assumption is quite strong, being weakened in several studies; for example, see the papers [23, 24].

Further, we discuss two basic updating models for the agent's beliefs, in which particular assumptions about the agent's awareness structure are introduced, and there is no information interaction between different agents.

3.2. Basic Updating Models for Agent's Beliefs

Consider two basic updating models for the agent's beliefs. They can be briefly described as follows. In the elementary binary model, the state of the world takes two values (the state is discrete), and each agent receives a binary signal about the state of the world; in the Gaussian model, the state of the world and private signals are realizations of Gaussian random variables.

In *the binary model*, the set of admissible states is $\theta \in \{\theta_0, \theta_1\}$, where $\theta_0 < \theta_1$; in the elementary statement, $\theta \in \{0, 1\}$. The probability distribution is characterized by one number–the probability of state 1. Private signals take the value 1 or 0 with the probabilities $P(s = 1|\theta = 1) = q$ and $P(s = 0 \mid \theta = 0) = q'$. A private signal is called *symmetric* if $q = q'$. In this case, the parameter q is called the signal accuracy. (A conventional assumption is $q > ½$.)

For the binary model, Bayes' rule can be written as the likelihood ratio

$$\frac{P(\theta=1\,|\,s)}{P(\theta=0\,|\,s)} = \frac{P(s\,|\,\theta=1)}{P(s\,|\,\theta=0)} \cdot \frac{P(\theta=1)}{P(\theta=0)}.$$

In the binary model, the signal leads to a bounded change of beliefs. If μ is the subjective belief about state 1, its variance is $\mu(1 - \mu)$. This means that new information can increase the variance and decrease the confidence in the resulting estimate. For a sequence of signals $\{s_t\}$ with the same accuracy q, Bayes' rule is applied sequentially. As $t \to \infty$, the agent's belief $\mu_t \to \theta$, and the variance of the estimate tends to 0.

In *the Gaussian model*, the state of the world is a realization of a Gaussian random variable or vector. In the simple case, $\theta \sim N(m, \sigma_\theta^2)$. The distribution *accuracy* is denoted by $\rho_\theta = 1/\sigma_\theta^2$. The private signal $s = \theta + \epsilon$ obeys the Gaussian distribution, where the noise is $\epsilon \sim N(0, 1/\rho_\epsilon)$. After receiving signal s, the updated distribution θ remains Gaussian $N(m', 1/\rho')$ with the parameters

$$\rho' = \rho + \rho_\epsilon,$$

$$m' = \alpha s + (1-\alpha)m, \text{ where } \alpha = \rho_\epsilon/\rho'.$$

Consequently, in the elementary Gaussian learning model, observations lead to an increase in the accuracy of the agent's beliefs (decrease in the variance); the posterior expectation of θ is the weighted sum of the signal and the prior expectation (with weights reflecting the accuracy).

Thus, in the basic learning models, an agent receives a sequence of informative signals and gradually reaches a true estimate for the state of the world. Let us now consider the formation of various information communities in these models.

3.3. Forming Different Information Communities

The question arises: can Bayesian agents[4] reach different beliefs if they receive the same information (the same sequence of signals) about the state of the world?

Cognitive limitations

Agents can reach different beliefs if *their prior beliefs differ* and *their memory is limited*. In [25], some of the agent's signals on the state of the world were supposed to be ambiguous and interpreted differently depending on their current beliefs. In particular, at a time instant t, an agent can receive informative signals a or b about the state of the world, or an ambiguous signal ab, which has to be interpreted and memorized as a or b due to the agent's memory limit. An agent forms a belief λ about the state of the world by Bayes' rule, interpreting the incoming signal ab as a if $\lambda_{t-1} > 1/2$, or as b if $\lambda_{t-1} < ½$. (Thereby, the agent shows the inclination to confirm his point of view.) Let the agents have different prior beliefs (for example, the first agent considers state A to be more likely, and the second agent, state B). If the probability of ambiguous signals is significant, then the agents will reach opposite beliefs about the state of the world with a positive probability.

Cognitive biases

In the paper [26], *the effect of an agent's inclination to confirm his point of view* was described within the binary model. The following assumption was introduced to model the inclination: if an agent receives a signal contradicting his belief about the state of the world, he incorrectly interprets (perceives) this signal with a probability $q > 0$ as confirming his belief. At the same time, he is unaware of the signal misinterpretation and acts like a typical Bayesian agent. As was established therein, under the agent's inclination to confirm his point of view (expressed by the parameter q), he can eventually reach the false belief, despite an infinite sequence of informative signals perceived by him. Accordingly, individual probabilities q can lead to some disagreement among agents in society.

Complex model of beliefs: additional factors and questions

As was demonstrated in [27], in some cases, the intensification of disagreement among individuals observing the same information is rational if they make *different assumptions about additional factors affecting the relationship between the parameters under consideration: the state of the world and the received*

[4] Although this subsection deals with situations with two agents, the considerations are applicable to any set of agents of two types.

signal (i.e., the private beliefs about the problem situation are richer compared to the individuals in classical learning models). This aspect was touched upon in [28], where the role of beliefs about an "auxiliary" issue (not directly related to the "main" issue but affecting the interpretation of signals associated with it) was considered. These beliefs may cause the polarization of beliefs about the main issue. With strained interpretation, due to the specifics of the agent's utility function, this class of models includes the model [29], in which the state of the world θ = (α, β) is a realization of the random variable $\tilde{\theta} = (\tilde{\alpha},\ \tilde{\beta})$, $\tilde{\alpha}, \tilde{\beta} \in \{0,\ 1\}$, and agents with different private signals on α, receiving general signals on β, reach different beliefs about the optimal actions.

Different prior beliefs

The paper [30] considered the polarization of Bayesian individuals' beliefs in a collective choice problem that depends on the state of the world and requires a decision (the choice of some policy). Depending on their beliefs about the state of the world, voters support one or another alternative. Then they observe the degree of success of their choice (the result of the chosen policy) and correct their beliefs about the state of the world. Polarization is excluded if and only if the conditional density of the choice result (given the state of the world and the chosen policy) has *the Monotone Likelihood Ratio Property* (MLRP). Otherwise, polarization cannot be ruled out even under small *differences in the prior beliefs*: the corresponding examples were provided for discrete and continuous indicators of the success of the chosen policy.

Different prior beliefs about conditional signal distributions

Agents can also reach some disagreement if their prior beliefs about the state of the world and their *beliefs about the conditional signal distributions* are different. Let us discuss this aspect in detail.

In [31], a learning model with two Bayesian agents (1 and 2) was considered. The agents observe a sequence of signals $\{s_t\}_{t=0}^{n}$, $s_t \in \{a, b\}$, from an environment. The state of the world is described by the parameter $\theta \in \{A, B\}$ (the true state is A), and the prior belief of agent i about the probability that $\theta = A$ is given by the parameter $\pi^i \in (0,1)$. The agents suppose that for a given parameter θ, the incoming signals are independent and identically distributed: $P(s_t = a \mid \theta = A) = p_A$ and $P(s_t = b \mid \theta = B) = p_B$. Usually, these probabilities are considered known. In reality, however, there may exist an uncertainty of the probability p_θ ($\theta \in \{A, B\}$): for each agent i, this uncertainty is described by his distribution of subjective probabilities F_θ^i.

Consider an infinite sequence of signals $s \equiv \{s_t\}_{t=1}^{\infty}$, and let S be the set of all such sequences. The posterior belief of agent i about the parameter θ given the observed sequence of signals $\{s_t\}_{t=1}^{n}$ is

$$\phi_n^i(s) \equiv P^i\left(\theta = A \middle| \{s_t\}_{t=1}^{n}\right).$$

Recall that the signals are independent and identically distributed. Hence, the posterior probability depends on the number of signals $s_t = a$ by a time instant n:

$$r_n(s) \equiv \#\{t \le n \mid s_t = a\}.$$

According to the strong law of large numbers, $r_n(s)/n$ converges with probability 1 to some frequency $\rho(s) \in [0,\ 1]$ for all agents. Defining the set $\bar{S} \equiv \{s \in S\colon \exists \lim_{n\to\infty} r_n(s)/n\}$, we write

$$\phi_n^i(s) = \frac{1}{1 + \frac{1-\pi^i}{\pi^i}\frac{P^i(r_n \mid \theta = B)}{P^i(r_n \mid \theta = A)}},$$

where $P^i(r_n|\theta)$ is the probability of observing exactly r_n signals $s_t = a$ in the sequence of the first n signals given F_θ^i.

As it turned out [31], if for each F_θ^i we have the probability $F_\theta^i(\hat{p}_\theta) = 1$ for some $\hat{p}_\theta > 1/2$ and $F_\theta^i(p) = 0$ for all $p < \hat{p}_\theta$, then: $P^i\left(\lim_{n\to\infty} \phi_n^i(s) = 1 \middle| \theta = A\right) = 1$ (*asymptotic learning*) and $P^i\left(\lim_{n\to\infty} \left|\phi_n^1(s) - \phi_n^2(s)\right| = 0\right) = 1$ (*asymptotic agreement*) for each $i = 1, 2$. Thus, if the individuals know the conditional distributions of signals (which are the same for them), they will learn the true state of the world from observations (almost surely as $n \to \infty$) and reach a consensus regarding the state θ in the case of observing the same sequence of signals. If the limiting frequency of the signal a is $\hat{p}_A$, then the individual believes that θ = A; if this frequency is $1 - \hat{p}_B$, then he believes that θ = B. The probability of all other cases for the agent is 0. If for sufficiently large $n < \infty$, the individuals observe ρ (the frequency of the signal a) different from $\hat{p}_A$ and $(1 - \hat{p}_B)$, they will associate this deviation with sampling variation. However, as the sample grows ($n \to \infty$), it becomes difficult to explain by the sample variation the signal frequency differing from $\hat{p}_A$ and $(1 - \hat{p}_B)$. Therefore, a natural approach is when the individuals are allowed to specify positive (albeit small) probabilities for all admissible values of p_θ. This assumption leads to various consequences; see below.

Theorem 1. *Assume that for each agent i and each value of the parameter* θ, *the probability distribution* F_θ^i *has a continuous, nonzero, and finite density function* f_θ^i *on the interval* [0, 1].

Then for $s \in \bar{S}$:

(a) *There is no asymptotic learning, i.e.,* $P^i\left(\lim_{n\to\infty}\phi_n^i(s)\neq 1|\theta=A\right)=1$.

(b) *There is no asymptotic agreement between two agents, i.e.,* $P^i\left(\lim_{n\to\infty}\left|\phi_n^1(s)-\phi_n^2(s)\right|\neq 0\right)=1$ *whenever* $\pi^1\neq\pi^2$ *and* $F_\theta^1=F_\theta^2$ *for each value* $\theta\in\{A,B\}$ [31, 32].

of p_θ. This assumption leads to various consequences; see below.

In fact, learning under such uncertainty can *intensify the disagreement between two Bayesian agents after receiving the same infinite sequence of signals*. This effect is impossible within the standard model; see the next theorem.

Theorem 2. *Assume that for each agent i and each value of the parameter* θ, *the probability distribution* F_θ^i *has a continuous, nonzero, and finite density function* f_θ^i *on the interval* [0, 1]. *In addition, assume that there exists a number* $\epsilon > 0$ *such that* $\left|R^1(\rho)-R^2(\rho)\right|>\epsilon$ *for each frequency* $\rho\in[0,1]$, where $R^1(\rho)\equiv f_B^i(1-\rho)/f_A^i(\rho)$ *is the likelihood ratio. Then, there exists an open set of prior beliefs* π^1 *and* π^2 *such that for all signals* $s\in\bar{S}$, $\lim_{n\to\infty}\left|\phi_n^1(s)-\phi_n^2(s)\right|>\left|\pi^1-\pi^2\right|$; *particularly,* $P\left(\lim_{n\to\infty}\left|\phi_n^1(s)-\phi_n^2(s)\right|>\left|\pi^1-\pi^2\right|\right)=1$ [31].

Thus, even small differences in the prior beliefs of agents lead to different interpretations of the signals. If the initial discrepancy is small, then the disagreement between the agents will intensify after almost any sequence of signals.

There is no network interaction among the agents in the models of learning and formation of information communities discussed above. In the general case, individuals—members of society—interact with each other within a social network. Hence, the actions of neighbors in the network can provide an agent with additional information about the state of the world. This type of interaction will be discussed in part II of the survey.

CONCLUSIONS

In part I of the survey, the concept of an information community has been outlined, and relevant models for forming the beliefs of individuals who seek to eliminate uncertainty about a given issue(s), eventually forming information communities, have been considered. Approaches to model the updating of private beliefs and the influence of various factors on the achievement of true beliefs and the formation of one or several different information communities in the network have been described. In a society of Bayesian agents, a true belief about the issue is often reached; for the emergence of various information communities, it is necessary to weaken the rationality requirement for individuals and/or introduce assumptions about different awareness of individuals.

Part II of the survey will consider the formation of information communities in network models with Bayesian agents and with naive (“heuristic”) individuals. Finally, part III of the survey will be devoted to empirical studies on the existence of information communities in real social networks and their features.

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