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USING ASSOCIATIVE NETWORKS TO REPRESENT ADOPTERS' BELIEFS IN A MULTIAGENT MODEL OF INNOVATION DIFFUSION

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A lot of agent-based models were built to study diffusion of innovations. In most of these models, beliefs of individuals about the innovation were not represented at all, or in a highly simplified way. In this paper, we argue that representing beliefs could help to tackle problematics identified for diffusion of innovations, like misunderstanding of information, which can lead to diffusion failure, or diffusion of linked inventions. We propose a formalization of beliefs and messages as associative networks. This representation allows one to study the social representations of innovations and to validate diffusion models against real data. It could also make models usable to analyze diffusion prior to the product launch. Our approach is illustrated by a simulation of iPod™ diffusion.

Keywords: Agent-based modeling; diffusion of innovations; knowledge representation.

1. Why Represent Beliefs?

Diffusion of innovations is an interdisciplinary field that studies "the spread of new ideas, opinions, or products throughout a society" [19] Rogers defines diffusion as "the process by which an innovation is communicated through certain channels over time among the members of a social system" (Ref. 17, p. 11).

Several models were built to study diffusion of innovations, including multiagent-based simulations, with different purposes. *Explicative models* aim to reach a better understanding of how individual interactions make collective dynamics appear. A great part of these models studies the decision/judgment level (adoption, opinion, perceived utility [7], payoff [3], attitude, etc.). For instance, in the threshold model (see e.g. Ref. 6), social pressure causes individuals to be influenced by opinions of their neighbors. Several models also include the beliefs level, i.e. what individuals trust for a given object (one uses "belief" rather than "knowledge" because these beliefs can be false or subjective). This is the case with models focused on informational cascades (see Ref. 16 for a review) or in the consummate approach [9]. In these models, beliefs are represented as single values or as a vector of values, and rarely aim to be matched against data collected on the field.

Predictive models aim to produce an estimation of the future diffusion rate of an innovation. The well-known model, and the most-used in industry, is the Bass aggregative model [4]. It includes parameters for adoption due to media messages, adoption due to interpersonal communication and an index of market potential for the new product. It permits one to reproduce the classical S curve of cumulated adoption.

Despite the large amount of literature about diffusion of innovations, there still remain several problems that have not been studied. The first lack resides in *explicative power*. Rogers [17] underlines that models are not able to explain innovation failures (sometimes due to misunderstanding of what innovations are or to incompatibility with beliefs or values). He also remarks that most of the said "innovations" launched in markets are in fact incremental products. In this case people already understand what the innovation is and how it works, so the diffusion becomes quicker. Such processes cannot be modeled without representing beliefs of the population about innovations. The second lack is about *predictive power*. The Bass model can predict the future adoption rate of an innovation only after its launch, based on the adoption data from innovators and early adopters. But, at this time, costs are already engaged (for building the product, for communication, etc.). Obviously, the predictive interest of the model is highly lowered. So, firms use less formal methods to test new concepts, like interviews or focus groups, which provide some insights into subjective perception and expectations about the innovation. Here again, it seems that modelers cannot avoid representing beliefs.

Our main concern is to be able to tackle real-world cases. In this paper we study how a modeler can represent individual beliefs in an agent-based simulation. For such a simulation, we need a model for knowledge representation that is complex enough to be explicative and representative, but also simple enough to make its parameters' settings and data collection possible. We illustrate this approach with the simulation of iPod$^{\mathrm{TM}}$ diffusion using beliefs collected across forums.

2. Model

2.1. *Beliefs as associative links*

2.1.1. *Individual associative network*

The concept of the associative network has been widely used in social sciences and artificial intelligence to model beliefs: Bayesian networks, causal networks, social representations represented as proximity networks, etc. A marketing methodology called the means-end chains theory (MCT) [15] proposes formalizing the perception of products as cognitive chains linking concrete attributes to perceived consequences for the individual and satisfaction of his values. As shown by the MCT, associative

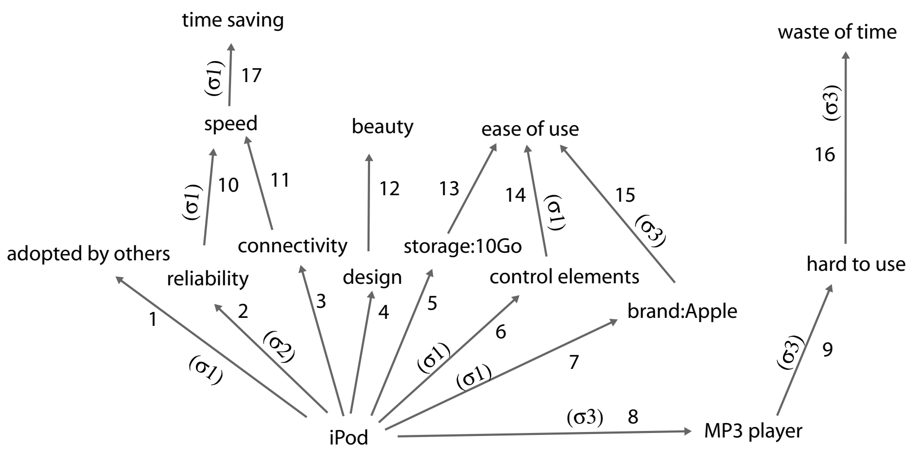

Fig. 1. Example of an individual associative network (IAN) retrieved by an interview for iPod$^{\text{TM}}$ (study of what people like or dislike for this product). To improve lisibility, only useful supports are provided. σ_1 represents the support "personal experience," σ_2 means "indirect experience" and σ_3 "no credibility."

networks are relevant to representing the beliefs about products (an example is provided in Fig. 1). These chains can be retrieved by semidirected interviews, surveys or statistical data analysis. Messages like advertisements or consumer reviews can also be represented as chains [14], as shown in Fig. 3.

Associative networks permit one to represent several kinds of knowledge. We categorize knowledge as private, concrete or subjective.[a] The subjective part of information is about the innovation itself, like product attributes (links 2–7) and perceived functional consequences of the product (e.g. 11, 13). This kind of information is received or retrieved by individuals through mass media or interpersonal communication. The private part of beliefs is about individuals themselves. These beliefs are more stable for an individual across time [12]. For instance, the belief "speed → time saving" is used for all technological innovations. Private beliefs can be heuristics, like "high price → high quality." They are provided as initial data by the modeler based on the population segmentation. The last kind of beliefs is about abstract judgments and is built by the individual himself based on his local information, as "product adopted by others." This knowledge is represented in agents by simple computational rules held by each agent.

From the modeler viewpoint, concepts in the model are a finite set $\mathcal{C}$, which is created based on data collection or expert hypothesis. Sometimes two or more concepts are incompatible: an agent cannot trust the two of them at the same time for the same social object. As in theory of evidence, we define frames of exclusivity

[a]This taxinomy follows the one provided by Audenaert and Steenkamp's studies of the MCT [2], and the discussion in the field of consumer value [8], which concludes that perceived value depends both on the intrinsic product properties and on the subjective perception of consumers.

called $\Theta^{\mathcal{X}}$, with $\mathcal{X} \subset \mathcal{C}$. Some examples of frames are: (solid, breakable), (good connectivity, bad connectivity).

Formally, we define knowledge as directed associations between concepts. Mathematically, a belief is a binary relation in $\mathcal{C}^2$. $C_1\ b_\sigma^{a,t}\ C_2$ is the conviction held by an agent $a \in \mathcal{A}$ at time t that two concepts (C_1 and C_2) $\in \mathcal{C}^2$ are associated with a given support $\sigma \in \Sigma$. The support represents the confidence of the agent in this belief (more details on support are provided below). In this model, existence of a link represents belief. No link means ignorance. Disbelief is modeled as the belief in the opposite concept. Each individual possesses his own set of beliefs; we name this set an individual associative network (IAN).

Some concepts are considered as objects of interest by the agents $\mathcal{A}$ (agents will speak about them, and they want to understand them, and they can take decisions about these concepts). We use a psychosocial term [10] to design these objects of common interest: these concepts are *social objects* $\mathcal{O} \subset \mathcal{C}$. When we model the diffusion of innovations, social objects are innovations. A set of beliefs about a social object o forms the *representation* $R_o^{a,t}$ of this object. This representation is the subgraph rooted in the social object. If a representation is shared between several agents, it becomes a *social representation* in the social psychology meaning, denoted as $SR_o^{\mathcal{X},t}$, with $o \in \mathcal{O}$, $\mathcal{X} \subset A$.

2.1.2. *Beliefs revision*

Insights into persuasive communication are provided by social psychology [10]. The persuasiveness of a communication depends on properties of the source like credibility, expertise, self-interest, structure of argumentation, or message order. No formal model exists for computing the total persuasiveness of a communication based on these parameters. However, several formalisms are available for representing beliefs and their strength, mainly with probabilities or belief functions (see Ref. 18 for a comparative review). But all of these models are normative and lead to results incompatible with observable evidence. They would require us to include quantitative valuation of beliefs (as probabilities or belief masses), which would make the model harder to validate, less representative and harder to manipulate. So, we developed a solution based only on the qualitative properties of beliefs.

The sources of information are perceived as more or less credible by individuals. Broadly speaking, personal experience is stronger than other advices, themselves stronger than advertisement. We define a set Σ that contains several levels of support (in other words: credibility, certainty, revisability, strength). Each source of information is categorized by the agents in one of these levels. Levels are defined operationally to fit observations from the population and the needs of the model. Currently we work with the following levels: *no credibility* is used for information from advertisement, *plausible* is used for advice from someone, *indirect experience* represents feedback of someone based on his personal experience. *Personal* *experience* represents the strongest level for beliefs acquired by the agent's direct experience.

We assume that a stronger source erases the previous advice, because the new source is considered to be more credible. In some cases, however, it is possible for a strong belief (acquired by direct experience) to be modified by new, weakly supported information, because individuals accept revision of old beliefs, comply with the social consensus, and can be convinced by a good argumentation or another reason. That is why we choose to model belief revision based on probabilities of revision between support categories $p\,(\text{revise}|\sigma_{\text{old}}, \sigma_{\text{new}})$. We built this function (Table 1) based on qualitative observations. A weak support has a low probability of modifying a stronger support. However, in the long term, this probability becomes higher and higher, leading to invalidation of old beliefs. This model is easier to validate than a quantitative representation of strength.

2.1.3. *Retrieving from memory*

We need to be able to retrieve the representation of a social object contained in an IAN. Retrieving a representation is a spreading activation process: start from the social object, then browse all the links connected to this node to build the representation $R_o^{a,t}$. We assume an activation propagation inspired by evidence networks: *the activation strength of a concept for an object is the strength of the weakest link in the chain that links the social object to this concept.* When activation follows a link, activation is filtered by the belief strength. For instance, in Fig. 1, activation of the concept "time saving" for the social object "iPod" is "indirect experience," which is the lowest support in the chain (σ_2). If a node receives several levels of activation from its parents, the stronger activation is kept (MAX activation, which is also an OR logical interpretation). In the example of Fig. 1,"ease of use" has a support of "personal experience." As a result, the *activated representation* contains the beliefs activated and their support.

In the particular case of incompatible beliefs, the activation process keeps only the strongest belief. For instance, in Fig. 1, the frame of exclusivity $\theta_{\text{complexity}} = \{\text{ease of use, hard to use}\}$ forbids these two concepts from being trusted at the same time. The spreading activation process sets a low activation to "hard to use" and a higher one to "ease of use," so only the last one will be included in the activated representation.

Table 1. Probability of revising a belief based on the support level of the previous belief σ_{old} (top) and on the support level of the new information σ_{new} (leftmost column).

	No credibility	Plausible	Indirect experience	Personal experience
No credibility	0.9	0	0	0
Plausible	1	0.9	0.01	0.001
Indirect experience	1	1	0.9	0.001
Personal experience	1	1	1	0.9

2.2. Communication

As shown before by the agent-based modeling community, the social structure has a huge impact on the system dynamics (see e.g. Ref. 19). A model of communication which is too simple — like a random meeting or cellular automata — does not seem adequate. As a consequence, we detail here explicitly the channels that support communication, the structure of messages themselves, and the topics (social objects) which agents are talking about (see Fig. 2).

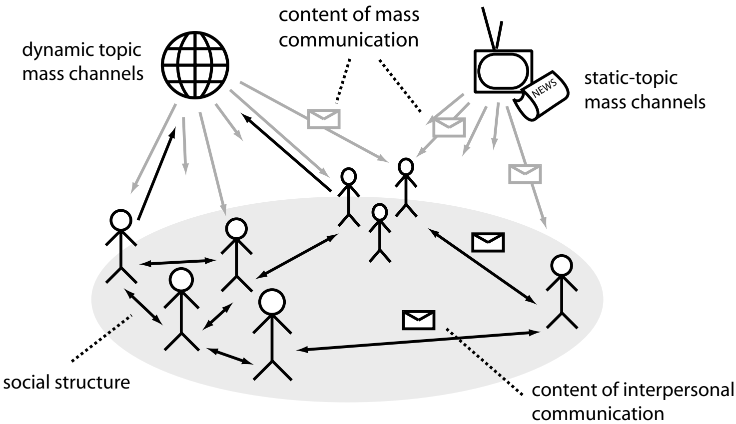

Fig. 2. Communication in a real population.

A channel is a support of communication that transmits information from an information source to an audience. Historically, mass media were controlled by firms for persuasive communication, while interpersonal channels were used only for uninterested communication. Today, individuals' reviews through specialized websites or forums could challenge traditional mass media, and interpersonal communication is beginning to be modified by individuals who are paid to propagate positive recommendations. To take this evolution into account, we propose categorizing channels based on their audience size and the determination of topics (Table 2). A unidirectional channel will always have a static topic (because the information source communicates about the object of its choice) while bidirectionnal channels allow interactive choice of topics. Modeling interactive topics implies modeling information research, and not only passive information reception.

A *mass channel* is connected to a great number of agents. The agent exposure defines its probability of receiving messages through this channel. An *interpersonal*

Table 2. Taxinomy of channels.

	Big audience	Small audience
Interactive topic choice	forums, search on internet	face-to-face
Static topic	press, advertisement, direct experience	weblogs

channel represents the fact that two individuals can exchange information with a given exposure parameter (the probability for the agents to meet). A static-topic channel will only passively transmit messages, so the topic is determined by the information source. An interactive-topic choice channel asks both agents which topics they want to discuss (the salient social objects set of each agent) and picks up randomly a social object in the union of the two sets.

2.3. *Messages*

Each transmission of information (either from mass media or interpersonal) is a message. A message is intended to transmit information[b] about a social object. It is sent by a sender over a channel; the audience will be determined by the channel itself. A communication campaign is composed of several messages broadcast on channels during a given period.

The content of a message is a *transmissible associative network* (TAN), which is madeup of associative links (see Fig. 3 for an example). A TAN typically embodies only a representation of a single social object. Sometimes — especially in the case of cobranding — the network can include several social objects and their associated representations. A TAN transmitted by an extrinsic information source is provided by the modeler. A TAN from an intrinsic information source is dynamically built by this agent.

2.4. *Agents*

A consumer agent represents a unit of adoption. It embodies a belief base, a list of currently salient social objects, and is linked to an agent profile. An agent profile contains the default exposure to mass channels, background knowledge, and subjective production of knowledge. It also contains functions to evaluate attractivity and

"The Apple ipod (20gb) is certainly one of the best mp3 players available today.
iPod supports up to 320kbps and even supports wav files for maximum quality... The only drawback to the sound quality is the sub-standard headphones which ship with product.

The iPod supports folders, excellent pc connectivity including USB 2.0 and Firewire support.
The battery will last for around 8-10 hours.
The product has NO support for protected WMA files."

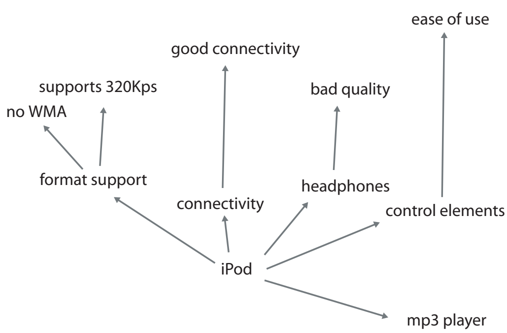

Fig. 3. Transcription of a consumer advice retrieved on a website (left) as a TAN (right).

[b]This definition of a message is voluntarily simplified to fit the frame of this paper. A message, especially an advertisement, also embodies some nonsemantical components.

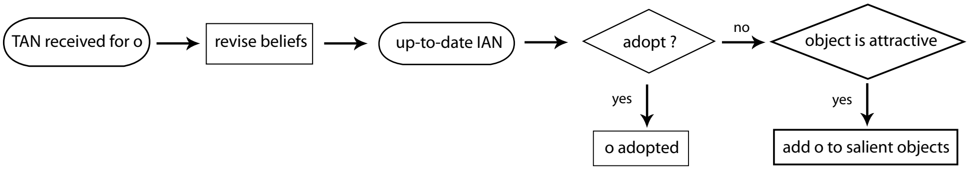

Fig. 4. Example of the decision process.

decide adoption. It can also include some rules to create the subjective knowledge based on local information. For instance, the fact that others have adopted a product (belief No. 1 in Fig. 1) is modeled by a threshold on the observed relationships that possess the product.

The definition of the agent's behavior is out of the scope of this paper. The modeler can implement whatever models he wants based on the internal representation of beliefs, which provides both beliefs and their strength. Several models exist for describing attitude formation or adoption based on beliefs, as the theory of planned behavior [1], the Fishbein model or any multicriterion model.

As an example we currently use the behavior process represented in Fig. 4. We designed multicriterion functions to compute attractivity and adoption, which take into consideration the support of beliefs.

Based on these three functions, the following process appears, which is compliant with existing models of buying steps or the adoption process [17]: (1) First, the agent becomes aware of the innovation, and receives prior information; (2) if the information is attractive enough, the agent decides to look for it; (3) if the agent thinks it has enough information, it decides to adopt or not; (4) using the product, it receives more information by usage and participates in word of mouth.

3. Application to iPod™

3.1. *Data collection*

We retrieved data from the published means-end chains analysis of iPod™ [13] and from statistical analysis of reviews provided by consumers on specialized websites. This data is used to determine the content of interpersonal messages and to insert background knowledge into agents. Associative networks permit one to represent background knowledge. For instance, in Fig. 1, the links (9, 16) represent the fears of the late majority about technology: it is hard to use and leads to a waste of time.

We identified the following static-topic mass channels: TV advertisement, generalist and specialized press, experience with the product. We set exposure to each medium from general statistics published about TV ad exposure, press reading, etc. We used as a social structure a small-world graph (a regular lattice with shortcuts, as proposed in Ref. 11). The exposure level to social interactions is retrieved from a study [5] about word of mouth, which quantifies on average 15 word of mouth episodes per week.

3.2. *Agent profiles*

We adopt the classical segmentation used in diffusion of innovations. *Innovators* like what is new, fun. They enjoy spending time to learn how an innovation works. They are able to understand technological terms. They read the specialized press nearly once a week. They are more impulsive than others, and can adopt an innovation as soon as it is available. They easily speak about innovations. They like to be alone in their possession of new things, and an innovation already possessed by others loses its attraction. *Early adopters* sometimes read the specialized press. They like new things, and they carefully study available information before buying. Individuals from the *early majority* like to be on-trend, with new products. They already have a good knowledge about technology, but like to have feedback from first adopters before buying. The *late majority* do not care about the novelty of a product. They focus on the utilitarian aspect, and do not like to lose time in learning new technologies. As part of their background knowledge, they believe that technological innovations are hard to use (as represented by beliefs 9 and 16 in Fig. 1). They consider a piece of information as true only if it comes from someone else with direct experience. *Laggards* have a low exposure to the press, and retrieve most of their information from interpersonal communication.

3.3. *Simulation*

The model is implemented with the repast framework. In this discrete-time simulation, each step represents one week.

Figure 5 shows the output of the model. Awareness starts before adoption due to announcement information transmitted about iPod$^{\text{TM}}$. Because an announcement is transmitted only in the specialized press, mainly innovators and early adopters are aware of the product and can propagate word of mouth around. Then the product is launched, with information in the generalist press and TV advertisements. All the population becomes aware of the product and can adopt it. The early majority require indirect information from previous users or independent reviews to adopt it. The late majority need indirect feedback to adopt it. The last curve in the figure shows that the diffusion is made quicker if another medium (here, the Internet) permits one to retrieve other advices quicker than face-to-face communication; this medium is highly efficient because it permits one to interactively determine topics and to retrieve credible information.

3.4. *Observations*

3.4.1. *How to improve diffusion?*

In this model an advertisement on its own does not lead to adoption, but can make the product salient in individual minds and provoke adoption or word of mouth. The best way to make diffusion quicker is to facilitate word of mouth, which is required to persuade the late majority and laggards to adopt the product.

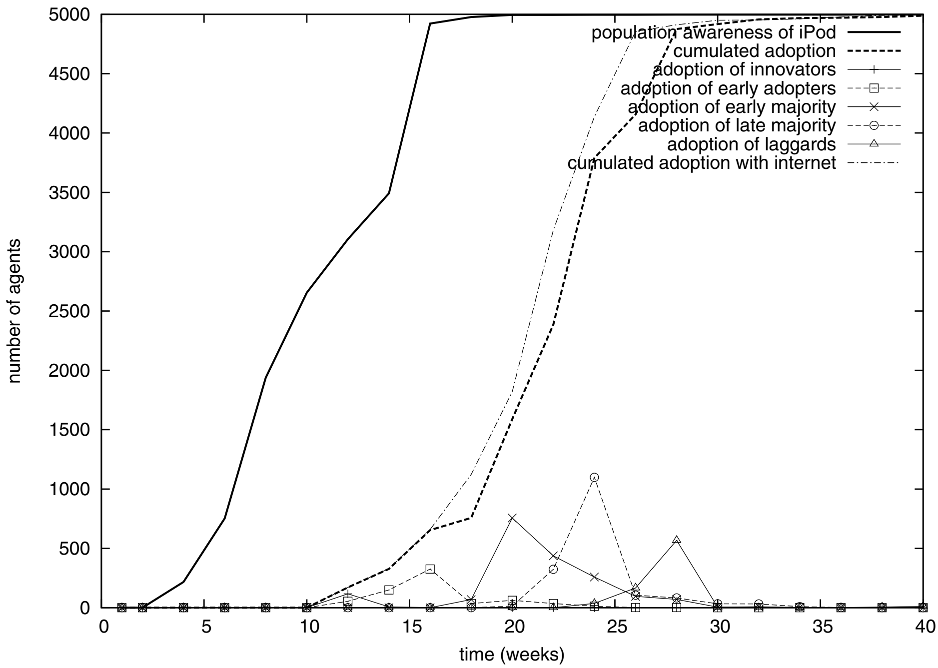

Fig. 5. Simulation of iPod$^{\text{TM}}$ diffusion in a population of 5000 agents.

Good timing and attractive information are required to stimulate word of mouth. If new information is sent when individuals are still looking for information, then this new information will be transmitted quickly through interpersonal communication. Observability, one of the factors mentioned by Rogers, also facilitates diffusion in this model. In the case of iPod$^{\text{TM}}$, the white hearspeakers are easily identifiable, and are related to iPod$^{\text{TM}}$ based on advertisement campaigns. So potential adopters are aware of others, adoption, leading them to follow this indirect recommendation. The importance of usage value, as in reality, is confirmed, because individuals who use the products are highly credible and can provoke adoption; it is of prime importance that they are satisfied by the product.

Social representations of the innovation appear in the model. At the beginning of diffusion, we can observe collective representations shared by several agents (Fig. 6): individuals who have already adopted the product possess a large amount of information provided by experience, while others have only a representation created by advertisement. Individuals who had no knowledge about MP3 players discover through word of mouth what the criteria for evaluating the innovation. While the late majority are initialized with no knowledge about MP3 players, all individuals end with general considerations about autonomy or storage capacity. We also observe examples of incomprehension: an individual who has no knowledge about storage capacity is unable to understand "10 Gb," but he will learn it through

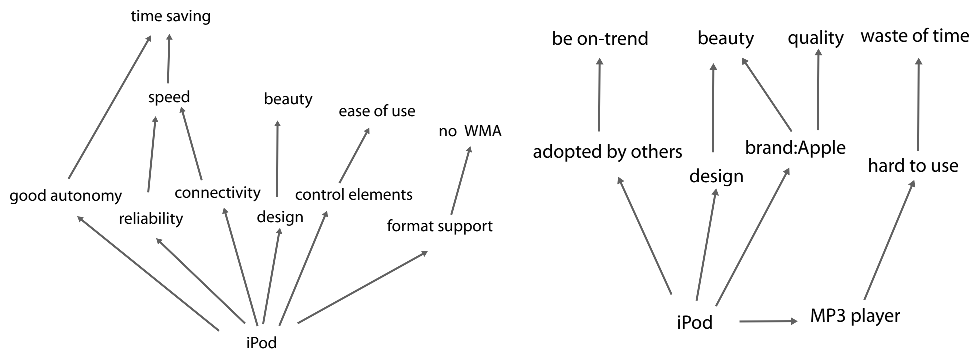

Fig. 6. Example of social representations. The left representation $SR_{\text{iPod}}^{\text{early adopters},12}$ is shared by first adopters who already have an experience with iPod$^{\text{TM}}$. The right representation $SR_{\text{iPod}}^{\text{late majority},12}$ is held by several agents who just have information from advertisements, and know that iPod$^{\text{TM}}$ is already widely adopted.

interpersonal messages or well-designed advertisements (with the slogan "1000 songs in your pocket").

4. Discussion

Representing knowledge as associative networks permits one to create models which can be tested against real data, and to represent both messages and individual knowledge in a computationally tractable way. This representation is highly representative and manipulable, even for nonexperts. Implicitly it allows one to model misunderstanding of information, word of mouth or the launch of related innovations in a more plausible way — in fact, models that were expected by Rogers. Hence we could build models that represent the whole adoption process, from awareness to decision.

When a diffusion model is built to be used as a decision-support system, this approach is obviously more instructive. Through simulation the modeler is able to study the true parameters of diffusion of innovations (those mentioned by Rogers and used by marketers): What is the perception of products? In what way are consumers aware of a product? What is the background knowledge of individuals, and will they be able to understand information? Why does an innovation provoke word of mouth? Used before the launch of the innovation, the model can be parameterized from interviews — (for subjective perception of the innovation) and general information (for background knowledge), giving one an efficient methodology to test possible diffusion cases.

The main limitation of such a model is the state of knowledge about human behavior and social phenomena: insufficient information is available about the structure of real social networks, what provokes word of mouth, etc. Our future work will be focused on the validation of models based on associative networks, including interview protocols and statistical methods.

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