A Selective Attention-based, Multi-Agent, Travel Information System

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Abstract. We describe a selective attention-based, multi-agent, travel information system. This system involves a master agent and personal agents. The master agent collects selectively information from several information sources and sends it to the personal agents so that they can selectively deliver information to the several mobile devices owned by humans. The main agents' models are described namely those of beliefs, desires, feelings, and, with special emphasis, the computational model of selective attention. Then, we describe an experiment to evaluate the performance and the potential benefits of these personal selective attention agents for filtering out unnecessary traffic information for their human owners.

Keywords: Selective Attention, Surprise, Curiosity, Emotion, Cognitive Models, Agent Architectures

1 Introduction

The advent of information technology is a primary reason for the abundance of information with which humans are inundated. Contrary to what in general could be expected, a lot of recent studies confirmed what Alvin Toffler [23] predicted a few decades ago: the overabundance of information instead of being beneficial is a huge problem having many negative implications, not only in personal life, but also in organizations, business, and in general in the world economy.

In fact, many of the recent developments in information technology have also exacerbated the number of interruptions that occur in the work environment. Interruptions and distractions take many forms such as ringing text messages, instant messages, alerts to incoming e-mail, RSS feeds, not to mention "old media" sources as newspapers and magazines. This has negative consequences for companies of all sizes, with some large organizations losing billions of dollars each year in lower productivity [8]. This phenomena of "Interruption Overload" [13] is especially problematic (or dangerous) if the human agent is performing critical tasks like driving a car (for instance, there is evidence indicating that mobile devices are the cause of many vehicle accidents [22, 24]).

Actually, Advanced Travel Information Systems (ATIS) that are designed to assist travelers in making pre-trip and en-route travel decisions by providing them pre-trip and en-route information, constitute paradoxically a remarkable example of a domain in which the problems of information overload persist. The new wireless and web technologies are used both to gather traffic information (e.g., cell-phone probes, incident reports by cell phone users, GPS (Global Positioning System) / GIS (Geographic Information Systems) tracking for incident management) and disseminate it (e.g., Internet postings of up-to-date transit schedules, advice issued through on-board navigation systems, advisory services delivered through mobile phones, PDAs or Smartphones).

However, while these information systems can undoubtedly help humans perform better in these complex traveling scenarios, if the amount of information achieves a level that is unhandled, instead of being beneficial, it is a problem. Moreover, with the expected increase in the number of these travel information systems, in the number of the information technologies used to disseminate information and the countless kinds of information provided, this may become even worse.

Although, evolution already provided humans with the selective attention components that indicate which few aspects of the world are significant to the particular problems at hand, the amount of information received by those selective attention components may be itself a problem and compromise agents' performance. This is even more problematic because most of the time this information is provided in a way that affects especially the high level natural selective attention, which is involved in strategic cognitive choices such as the preference or shift of a task or activity over another.

Research proves that the brain simply does not deal very well with this multitasking process: there is a waste of time as the brain switches from one task to another and back again [8]. This explains why decision quality and the rate of performing tasks degrades with increases in the amount of information being considered.

A fundamental strategy for dealing with this problem of information overload [13] should include making devices that incorporate themselves selective attention agents in order to decrease the amount of information considered in their own reasoning/decision-making processes or decrease the amount of information provided by them to humans, preventing these from a number of interruptions.

More specifically, in the case of the travel information domain, it is contended that while many traveler information systems are innovative and make use of cutting edge technologies, they lack real machine intelligence and therefore may be limited in their ability to service the traveling public over the long-run. On the one hand, a wave of technological developments, in particular the increasing deployment of GIS and, on the other hand, the introduction and rapid market penetration of mobile devices such as cell phones boosted the development of ATIS towards what has been termed Intelligent Traveler Information Systems (ITIS) [1], in which artificial intelligence techniques are drawn upon to create systems capable of providing travelers with more personalized planning assistance.

But how to model selective attention in artificial agents? The problem starts at the human level. Although selective attention has been thoroughly researched over the last 100 years in psychology and more recently in neuroscience (e.g., [7, 25]), at present there is no general theory of selective attention. Instead there are specific theories for specific tasks such as orienting, visual search, filtering, multiple action monitoring (dual task), and multiple object tracking.

In this paper we describe selective attention-based, multi-agent, travel information system involving a master agent and personal agents. The master agent collects selectively information from several information sources and send it to the personal agents so that they can selectively deliver information to the several mobile devices owned by humans. An artificial selective attention mechanism is used by personal, artificial agents so that only cognitively and affectively, interesting/relevant information is selected and forwarded to the owners or users for whom the artificial agents might act on their behalf. Our approach relies on the psychological and neuroscience studies about selective attention which defend that variables such as unexpectedness, unpredictability, surprise, uncertainty, and motive congruence demand attention (e.g., [2, 7, 14]).

The next section describes from a general point of view the selective attention-based, multi-agent information system. The main agents' models are described namely of desires, beliefs, with special emphasis on the computational model of selective attention. Section 3 describes an instance of this information system: the selective attention-based, multi-agent, travel information system. Section 4 describes some experimental tests. Finally, section 5 presents conclusions.

2 A Selective Attention-based, Multi-Agent Information System

The Selective Attention-based Multi-Agent Information System architecture we propose involves a master agent and personal agents. The main role of the master agent is collecting selectively information from several information sources and sending it to the personal agents so that they can selectively deliver information to the several mobile devices owned by humans. Each personal agent models an user and acts on his/her behalf. For this reason it comprises the following models: (i) a model for beliefs/expectations, i.e., a model for representing and generating expectations; (ii) a model for representing desires and their dynamics; (iii) a model for feelings; and, (iv) a model for selective attention.

The next subsections describes the main models of the selective attention-based agents. It is worth noticing that the master also exhibits the same models with the exception of the model for representing and generating desires. Both kinds of agents interact with the external world receiving from it information through the senses and outputs actions through their effectors. Finally, it is important to say that we assume the world is described by a large amount of statistical experiments.

2.1 Modelling Beliefs/Expectations and their Generation

The representation of the agent's memory contents relies on semantic features or attributes much like in semantic networks [15] or schemas [17, 18, 20]. Memory elements are described by a set of attribute-value pairs that can be represented in a graph-based way [9]. Each attribute, $attr_i$, is viewed by us as a statistical experiment in that each attribute can have more than one possible outcome, each possible outcome can be specified in advance, and its outcome depends on chance. In this sense, each attribute is described by a probabilistic distribution, i.e., a set $A_i = \{< value_j, prob_j, desireStrength_j >: j = 1, 2, \ldots, n\}$, where n is the number of possible values of the attribute, $P(attr_i = value_j) = prob_j$, and $desireStrength_j$ is the desirability of $attr_i = value_j$ (for a related work see [16]). The belief strength of a an attribute value is given by its probability which is computed from data using a frequentist approach and generated or updated (depending on whether or not there was already that attribute-value pair associated with a probability value) as new information is acquired.

2.2 Modelling Desires and Desire Dynamics

While the belief strengths are inferred from data using a frequentist approach and updated as new information is acquired, the desirability of the outcomes can be previously set up or learned based on the intentions and contexts of the agent on which it depends, suffering changes whenever the agent is committed with a new intention and/or in a new context. For modelling this dynamics, we make use a desire strength prediction model (a model for generating desire strengths for all the outcomes of the statistical experiments of the world that are know given the desires of the agent, the intentions, as well as the context of the user (for more details see [5, 4]). As seen before, the desire strength is associated with each attribute together with the belief strength.

2.3 Modelling Feelings

The model of feelings receives information about a state of the environment and outputs the intensities of feelings. Following Clore [3], we include in this model affective, cognitive, and bodily feelings. The latter two categories are merged to form the category of non affective feelings. This means that this module is much broader than a module of emotion that could be considered. Feelings are of primary relevance to influence the behavior of an agent, because computing their intensity the agent measures the degree to which the desires are fulfilled. In this paper, we highlight the feelings of surprise, uncertainty, and pleasantness/unplesantness described in the context of the selective attention model presented in the next subsection.

2.4 Modelling Selective Attention

Selective attention may be defined as the cognitive process of selective allocation of processing resources (focus of the senses, etc.) on relevant, important or interesting information of the (external or internal) environment while ignoring other less relevant information. The issue is how to measure the value of information. What makes something interesting? In cognitive science, attentional focus is linked with expectation generation and failure, i.e., with surprise [14]. Therefore, it is reasonable to consider that any model of selective attention should rely on a cognitive model of surprise. However, surprise is not enough. Happiness/pleasantness, which according to cognitive theories of emotion and specifically to belief-desire theories of emotion [16] is directly related to congruence between new information and the human agent's motives/desires, may also play also a fundamental role on attention. For this reason, the system must also incorporate a measure of the expected satiation of the desires.

We assume that each piece of information resulting from this process, before it is processed by other cognitive skills, goes through several sub-selective attention devices, each one evaluating information according to a certain dimension such as surprise, uncertainty, and motive-congruence/incongruence – happiness. For this task the selective attention mechanism takes into account some knowledge container (memory — preexisting information), and the intentions and desires (motives).

The next sub-sections describe each one of the dimensions for evaluating information, namely surprise, uncertainty, and motive congruence/incongruence. While the dimensions of surprise and uncertainty are related to the value of information to the belief store of the agent, the dimension of motive congruence/incongruence is related to the value of information to the goals/desires of the agent (these dimensions are related to the concepts of cognitive and affective feelings of [3] and belief-belief and belief-desire comparators of [16]).

Surprise Value of Information We adopted the computational model of surprise of [10, 12] which is formally defined in Definition 1 (for related models see [11]). Macedo, Cardoso and Reisenzein computational model of surprise suggests that the intensity of surprise about an event E_g, from a set of mutually exclusive events $E_1, E_2, \ldots, E_m$, is a nonlinear function of the difference, or contrast, between its probability and the probability of the highest expected event E_h in the set of mutually exclusive events $E_1, E_2, \ldots, E_m$.

Definition 1. *Let (Ω, A, P) be a probability space where Ω is the sample space (i.e., the set of possible outcomes of the experiment), $A = A_1, A_2, .., A_n$ is a σ-field of subsets of Ω (also called the event space, i.e., all the possible events), and P is a probability measure which assigns a real number $P(F)$ to every member F of the σ-field A. Let $E = \{E_1, E_2, \ldots, E_m\}$, $E_i \in A$, be a set of mutually exclusive events in that probability space with probabilities $P(E_i) >= 0$, such that $\sum_{i=1}^{m} P(E_i) = 1$. Let E_h be the highest expected event from E. The intensity of surprise about an event E_g from E is given by:*

$$S(E_g) = \log(1 + P(E_h) - P(E_g)) \tag{1}$$

The probability difference between $P(E_h)$ and $P(E_g)$ can be interpreted as the amount by which the probability of E_g would have to be increased for E_g to become unsurprising.

Proposition 1. *In each set of mutually exclusive events, there is always at least one event whose occurrence is unsurprising, namely, E_h.*

Uncertainty-based Value of Information Information is a decrease in uncertainty which, according to information theory, is measured by entropy [21]. When new information is acquired its amount may be measured by the difference between the prior uncertainty and the posterior uncertainty.

Definition 2. *Let (Ω, A, P_{prior}) be a probability space where Ω is the sample space (i.e., the set of possible outcomes of the experiment), $A = A_1, A_2, .., A_m$ is a σ-field of subsets of Ω (also called the event space, i.e., all the possible events), and P_{prior} is a probability measure which assigns a real number $P_{prior}(F)$ to every member F of the σ-field A. Let $E = \{E_1, E_2, \ldots, E_m\}$, $E_i \in A$, be a set of mutually exclusive events in that probability space with probabilities $P_{prior}(E_i) >= 0$, such that $\sum_{i=1}^{m} P_{prior}(E_i) = 1$. Let P_{post} be the posterior probability measure, after some data is acquired, which assigns a real number $P_{post}(F)$ to every member F of the σ-field A such that it assigns $P_{post}(E_i) >= 0$ with $\sum_{i=1}^{m} P_{post}(E_i) = 1$. According to information theory, the information gain of an agent after some data is acquired, $IG(E)$, is given by the decrease in uncertainty:*

$$\begin{aligned} IG(E) &= H_{prior}(E) - H_{post}(E) \\ &= -\sum_{i=1}^{m} P_{prior}(E_i) \times \log(P_{prior}(E_i) - \\ &\quad (-\sum_{i=1}^{m} P_{post}(E_i) \times \log(P_{post}(E_i)) \end{aligned} \tag{2}$$

$H_{post} = 0$ if and only if all the $P_{post}(E_i)$ but one are zero, this one having the value unity. Thus only when we are certain of the outcome does H_{post} vanish, otherwise it is positive.

IG is not normalized. In order to normalize it we must divide it by $\log(m)$ since it can be proved that $IG \leq \log(m)$:

$$IG(E) = \frac{H_{prior}(E) - H_{post}(E)}{\log(m)} \tag{3}$$

Motive Congruence/Incongruence-based Value of Information While the measure of surprise takes into account beliefs that can be confirmed or not, the pleasantness function that we describe in this subsection takes as input desires that, contrary to beliefs, can be satisfied or frustrated. Following the belief-desire theory of emotion [16], we assume that an agent feels happiness if it desires a state of affairs (a proposition) and firmly beliefs that that state of affairs obtains. The intensity of happiness about an event is a monotonically increasing function of the degree of desire of that event as formally defined in Definition 4.

Definition 3. *Let (Ω, A) be a measurable space where Ω is the sample space (i.e., the set of possible outcomes of the experiment) and $A = A_1, A_2, .., A_m$ a σ-field of subsets of Ω (also called the event space, i.e., all the possible events). We define the measure of desirability of an event on (Ω, A) as $D : A \to [-1, 1]$, i.e., as a signed measure which assigns a real number $-1 \leq D(F) \leq 1$ to every member F of the σ-field A based on the profile of the agent, so that the following properties are satisfied:*

- $D(\emptyset) = 0$, $-|\Omega| \geq D(\Omega) \leqslant |\Omega|$
- *if $A_1, A_2, \ldots$ is a collection of disjoint members of A, in that $A_i \cap A_j = \emptyset$ for all $i \neq j$, then*

$$D(\bigcup_{i=0}^{\infty} A_i) = \sum_{i=0}^{\infty} D(A_i) \tag{4}$$

The triple (Ω, A, D) is called the desirability space.

Definition 4. *Let (Ω, A, P) and (Ω, A, D) be the probability and the desirability spaces described, respectively, in Definition 1 and Definition 3. Let $E = \{E_1, E_2, \ldots, E_m\}$, $E_i \in A$, be a set of mutually exclusive events in that probability space with probabilities $P(E_i) >= 0$, $\sum_{i=1}^{m} P(E_i) = 1$. If $P(E_g) = 1$, the intensity of happiness, i.e., motive congruence, about an event E_g from E is given by:*

$$MC(E_g) = D(E_g) \tag{5}$$

The Principle of Selective Attention Having defined the motive, the uncertainty-based, and surprise-based selective attention modules, we are now in a position to formulate, in a restricted sense (without the inclusion of other information measures such as complexity), the principle that a resource-bounded rational agent should follow in order to avoid an overabundance of information and interruptions in the absence of a model for decision-making. Note that if this model is known, the problem is reduced to the classical computation of the value of information that has been extensively studied (e.g., [6, 19]).

Definition 5. *A resource-bounded rational agent should focus its attention only on the relevant and interesting information, i.e., on information that is congruent or incongruent to its motives/desires, and that is cognitively relevant because it is surprising or because it decreases uncertainty.*

We may define real numbers α, β, and γ as levels above which the absolute values of motive congruency, surprise, and information gain (decrease of uncertainty), respectively, should be so that the information can be considered valuable or interesting. These are what we called the triggering levels of alert of the selective attention mechanism. Note that, making one of those parameters null is equivalent to removing the contribution of the corresponding component from the selective attention mechanism.

3 The Selective Attention-based, Multi-Agent, Travel Information System

We are developing an ITIS according to the generic selective attention-based, multi-agent information system described in the previous section (see Figure 1). There is a personal selective attention agent for each registered traveler. Each one of these personal agents has information about the expectations of its owner based on their travel history. The master agent is responsible for starting, not only the personal agents, but also the Web agents, described in Figure 1 as $\texttt{Agent}_{\texttt{POIs}}$ and $\texttt{Agent}_{\texttt{Traffic}}$. The system is capable of retrieving travel information from several location-based services, such as Foursquare API[1] (a location-based social network) and Bing Traffic API[2] (that provides information about traffic incidents and issues, e.g., construction sites and traffic congestion), among others. Physically, the master and the personal agents might inhabit in the same machine. This is the case of our ITIS: there is a server that accommodates both the master agent and the personal agents. There is also an interface of the personal agents that acts as a client and which is stored in mobile devices owned by humans.

Let us illustrate how the value of information is computed by the selective attention mechanism. Suppose that a traveller's navigation system provided the pre-route path containing a road A for an agent (a driver) based on its profile (e.g., preference for shortest routes). Suppose the agent has the following expectations for the traffic conditions of road A, for a certain period/time of the day for a certain day of the week: 60% of probability of "good traffic conditions" (event E_1), 30% of probability of "moderate traffic conditions" (event E_2), and 10% of probability of "bad traffic conditions" (event E_3). Suppose the desire strengths of these events are 1, -0.5, and -1, respectively. Given that the agent plans to go trough that route, suppose its module for generating/managing desires assigns a null desire strength for the other routes as it does not care about the traffic conditions of the other roads that are not part of its planned route.

[1] https://developer.foursquare.com/

[2] http://msdn.microsoft.com/en-us/library/hh441725

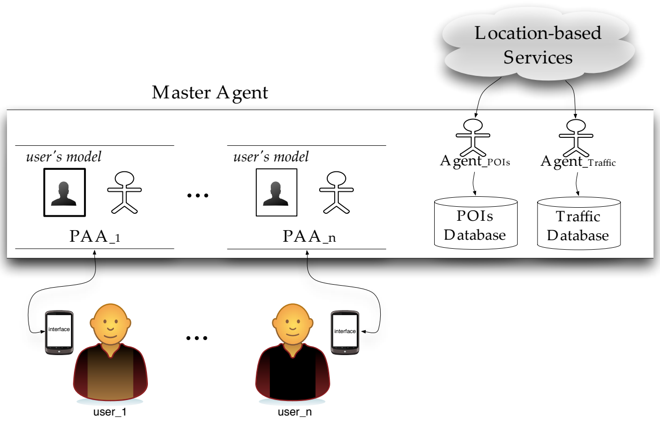

Fig. 1. System's Architecture.

What is the relevance of becoming aware that the current traffic conditions of road A are good (event E_1)? Considering solely the motive-based component, the outcomes (events E_1, E_2, and E_3) elicits happiness (motive congruence) with intensity 1, -0.5 and -1, respectively. E_1 is congruent/consistent with the goals of the agent, while E_2 and E_3 are incongruent with the goals of the agent.

According to Equation 1, the surprise value of E_1, E_2, and E_3 are, respectively, 0, 0.38, and 0.58. Illustrating for the case of E_3:

$$
\begin{aligned}
Surprise(E_3) &= \log(1 + P(E_1) - P(E_3)) \\
&= \log(1 + 0.6 - 0.1) = 0.58
\end{aligned}
\tag{6}
$$

According to Equation 3, the normalized information gain value of E_1, E_2, or E_3 is:

$$
\begin{aligned}
IG(E) &= \frac{H_{prior}(E) - H_{post}(E)}{\log(m)} = \frac{H_{prior}(E) - 0}{\log(3)} \\
&= \frac{-\sum_{i=1}^{3} P_{prior}(E_i) \times \log(P_{prior}(E_i))}{\log(3)} = 0.82
\end{aligned}
\tag{7}
$$

Assume the Principle of Selective Attention described above, with parameters $\alpha = 0.3$, $\beta = 0.5$, and $\gamma = 0.6$. Are all these events interesting? Considering the motive-based component all those events are interesting. However, from the perspective of the surprise-based selective attention component, the answer is "no" to the question related with the events E_1 and E_2 in that their surprise values, 0 and 0.38, respectively, are below β. With respect to E_3 the answer is "yes" given that its surprise value is 0.58. Taking the uncertainty-based component into account, the answer is "yes" for all the events because their occurrence gives a normalized information gain of 0.82 which is above γ.

4 Experimental Tests with Traffic Information

We conducted an experiment to evaluate the performance and the potential benefits of the personal selective attention agent for filtering unnecessary information for its owner (a human traveler). To do that we assessed its performance considering the opinions of the human travelers, by comparing their classifications about whether some information is relevant or not and the classifications of the selective attention agent. The selective attention agent is considered to perform erroneously if it filters a relevant information or if it does not filter an irrelevant information. The environment considered was Bissaya Barreto Avenue of the city of Coimbra, Portugal. We configured a selective attention agent to provide real time information about the traffic conditions in that street to 5 volunteer travelers whose path include that street. We collect information about the relevance of the information the agent delivered during 10 days at the same time (9h:00m) and always concerning the same street. In addition, after the trip, the information the agent did not delivered, when the value computed by its selective attention mechanism was below the triggering level of alert, was shown to the travelers. Then, these travelers were asked to rate the relevance they would had assigned that information, if it was delivered. All these data were used to compute the true and false positives.

Figure 2 presents the Receiver Operating Characteristic (ROC) curves of the selective attention agent using: (i) only surprise-based selective attention; (ii) uncertainty-based selective attention; (iii) both surprise and uncertainty-based selective attention.

As it can be seen there is a positive trade-off between benefits (true positives) and costs (false positives) of the selective attention mechanisms.

5 Conclusions

We described a two-parted agent architecture comprising an agent whose role is gathering travel information from different sources, and a set of personal assistant agents, each one representing and acting on behalf of a user so that only relevant information is delivered to the user. We presented an approach for filtering unnecessary information. We found evidence indicating that the mechanism contributes for decreasing the amount of unnecessary information while maintaining acceptable the performance of the owner (a human).

The advantages of reasoning correctly with less information include spending less time in processing information which is important in time-critical, high-risk situations. Besides, agents equipped with a selective attention filter can be successful personal assistants of humans, integrated for instance in mobile devices, so that their human users are prevented from unnecessary interruptions.

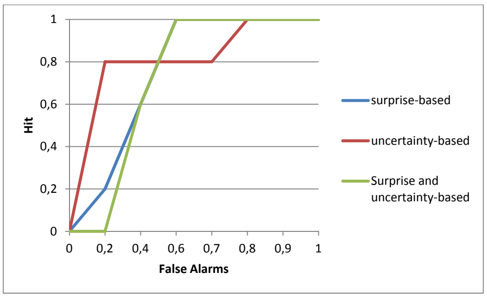

Fig. 2. ROC curves for the motive and surprise-based selective attention, for the motive and uncertainty-based selective attention, and for the motive, surprise, and uncertainty-based selective attention.

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