Overcoming Information Overload with Artificial Selective Agents: an Application to Travel Information Domain

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ABSTRACT

We describe an application of Macedo's computational model of selective attention for overcoming the problem of information and interruption overload of intelligent agents in travel information systems. This computational model has been integrated into the architecture of a BDI artificial agent so that this can autonomously select relevant, interesting travel information of the (external or internal) environment while ignoring other less relevant information. The advantage is that the agent can communicate only that interesting, selective information to its processing resources (focus of the senses, decision-making, etc.) or to its human owner's processing resources so that these resources can be allocated more effectively. We illustrate and provide experimental results of this role of the artificial, selective attention mechanism in the travel domain.

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous

General Terms

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Keywords

Information overload, Selective attention, Interest, Value of information, Surprise, Uncertainty, Resource-bounded agents, Personal agents

1. INTRODUCTION

The advent of information technology is a primary reason for the abundance of information with which humans are inundated, due to its ability to produce more information more quickly and to disseminate this information to a wider audience than ever before. Surprisingly, a lot of recent studies confirmed what Toffler [36] 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, research proves that the brain simply does not deal very well with a multitasking process [12]. 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 [24] 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.

But how to model selective attention in artificial agents? Although selective attention has been thoroughly researched over the last 100 years in psychology and more recently in neuroscience (e.g., [10, 38]), 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 spite of this, a number of models of selective attention has been proposed in Cognitive Science (e.g., [9, 21]). Particularly related with these models is the issue of measuring the value of information. A considerable amount of literature has been published on these measures, especially from the fields of active learning and experimental design. Most of those measures rely on assessing the utility or the informativeness of information (e.g., [8, 20, 13, 33]). However, little attention has been given to the surprising and motive congruence value of information, giving the beliefs and desires of an agent.

Macedo, Reisenzein and Cardoso (e.g., [16, 19]), and Lorini and Castelfranchi [14] proposed, independently, computational models of surprise that are based on the mechanism that compares newly acquired beliefs to preexisting beliefs. Both models of artificial surprise were influenced by psychological theories of surprise (e.g., [23]), and both seek to capture essential aspects of human surprise (see for a comparison [18]).

In this paper we describe the application of Macedo's artificial selective attention mechanism [15] to travel information systems. In our approach, artificial agents of travel information systems make use of that mechanism so that only cognitively and affectively, interesting/relevant travel information is selected and forwarded to drivers. The selective attention mechanism 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, 10, 25]).

The next section presents an overview of Macedo's computational model of selective attention. Section 3 illustrates how this selective attention mechanism can be used for filtering irrelevant information in the travel domain. Section 4 examines the performance of the selective attention mechanism as well as its role on the decrease of unnecessary information. Finally, in Section 5 we present conclusions.

2. SELECTIVE ATTENTION AGENT

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?

Macedo [15] developed previously an architecture for a personalized, artificial selective attention agent (see Figure 1). It is assumed that: (i) this agent interacts with the external world receiving from it information through the senses and outputs actions through its effectors; (ii) the world is described by a large amount of statistical experiments; (iii) the agent is a BDI agent [27], exhibiting a prediction model (model for generating expectations, i.e., beliefs about the environment), a desire strength prediction model (a model for generating desire strengths for all the outcomes of the statistical experiments of the world that are known given the desires of the agent – profile of the agent which include basic desires), as well as the intentions (these define the profile of the agent); (iv) the agent contains other resources for the purpose of reasoning and decision-making.

The first of the modules of the architecture (module 1 in Figure 1) is concerned with getting the input information. The second is the computation of the current world state. This is performed by generating expectations or assumptions (module 2), based on the knowledge stored in memory, for the gaps of the environment information provided by the sensors (module 1). 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 (module 4), uncertainty (module 5), and motive-congruence/incongruence – happiness (module 6). For this task the selective attention mechanism takes into account some knowledge container (memory — preexisting information (module 7)), and the intentions and desires (motives — module 8). There is a decision-making module (module 9) that takes into account the values computed by those sub-selective attention modules and decides if a piece of information is relevant/interesting or not. Then, this module of decision-making selects the more relevant pieces of information so that other resources (reasoning, decision-making, displaying, communication resources, etc.) (module 10) can be allocated to deal with them.

The process of making the right decision depends heavily on a good model of the environment that surrounds agents. This is also true for deciding in which information should the agent focus. Unfortunately, the real world is not crystal

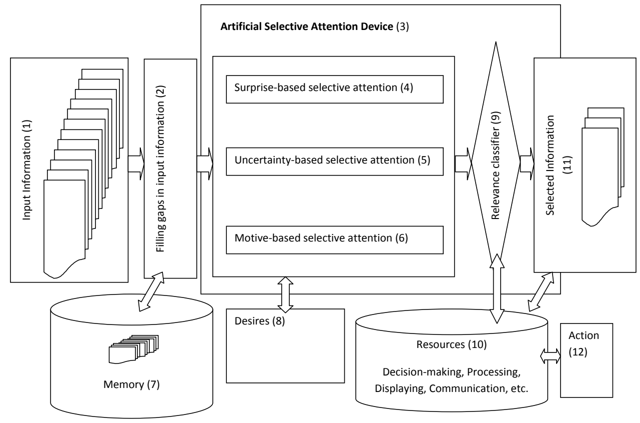


Figure 1: Architecture of an artificial selective attention agent.

clear to agents. Agents almost never have access to the whole environment, mainly because of the incompleteness and incorrectness of their perceptual and understanding components. In fact, it is too much work to obtain all the information from a complex and dynamic world, and it is quite likely that the accessible information suffers distortions. Nevertheless, since the success of agents depends heavily on the completeness of the information of the state of the world, they have to pursue alternatives to construct good models of the world even (and especially) when this is uncertain. According to psychologists, cognitive scientists, and ethologists [11, 26], humans and, in general, animals attempt to overcome this limitation through the generation of assumptions or expectations to fill in gaps in the present or future observational information. When the missing information, either of the present state of the world or of the future states of the world, becomes known to the agent, there may be an inconsistency or conflict between it and the assumptions or expectations that the agent has. As defended by Reisenzein [28], Gardenfors [7], Ortony and Partridge [25], etc., the result of this inconsistency gives rise to surprise which in our model of selective attention and according to previous studies plays a central role in selective attention. It also gives rise to the process of updating beliefs, called belief revision (e.g., [6]).

The representation of the memory contents (beliefs) relies on semantic features or attributes much like in semantic networks [31] or schemas [30]. Each attribute, $attr_i$, viewed by us as a statistical experiment, 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 [29]).

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, i.e., 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.

Much like the motivation system of Clarion [35], the module of desires encompasses explicit (goals) and implicit motives (basic desires). Following the pluralist view of motivation [22, 32, 37], the sub-module of basic desires (basic motivations/motives) contains a set of basic desires that drive the behaviour of the agent by guiding the agent to reduce or to maximize a particular feeling [17]. Among the basic desires we can find surprise and curiosity.

The module of feelings receives information about a state of the environment and outputs the intensities of feelings. Following Clore [3], we include in this module 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 and pleasantness/unplesantness.

Although the architecture of the computational model of selective attention includes all those above-mentioned sub-selective attention modules, we reserve some room in the architecture of the model for other sub-selective attention components, such as coping potential, complexity.

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 [29]).

2.1 Surprise Value of Information

We adopted the computational model of surprise of [16, 19] which is formally defined in Definition 1 (for related models see [18]). 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.

2.2 Uncertainty-based Value of Information

Information is a decrease in uncertainty which, according to information theory, is measured by entropy [34]. 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 $IG \leq \log(m)$:

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

2.3 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 [29], 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* $-1 \le D(F) \le 1$ *to every member* F *of the* σ*-field* A *based on the profile of the agent, so that the following properties are satisfied:*

- $D(\emptyset) = 0$
- *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*

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

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:*

$$MC(E_g) = D(E_g) \quad (5)$$

2.4 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., [8, 31]).

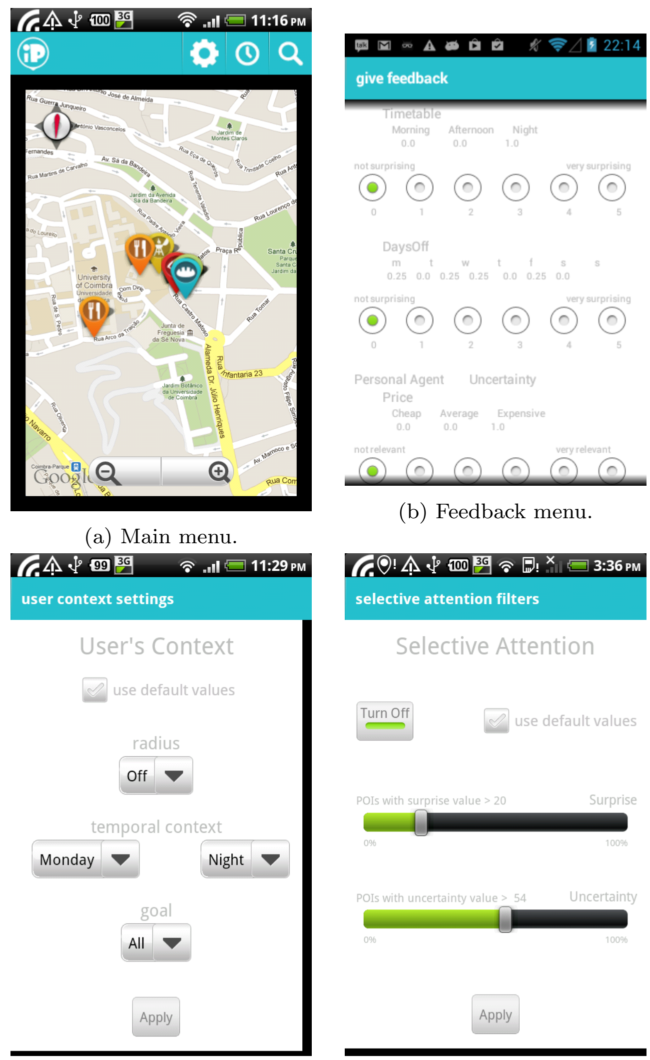
Definition 5. *A resource-bounded rational agent should focus its attention only on the relevant and interesting information, i.e., on information that is congruent or incongruent to its motives/desires, and that is cognitively relevant because it is surprising or because it decreases uncertainty.*

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 (for a different approach see Martinho and Paiva's attention grabbing mechanism [21] whose main feature is not relying on tuned parameters but on expectation and prediction error).

3. PRACTICAL APPLICATION

The Selective Attention-based, Multi-Agent, Travel Information System architecture (see Figure 4) we developed involves a master agent and personal agents (for related works on this domain see [1]). There is a personal selective attention agent for each registered traveler. Each personal agent models an user cognitively and motivationally and acts on his/her behalf, i.e., each personal agent has information about the expectations and desires of its owner based on their travel history. The main role of the master agent is collecting 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.

Physically, the master and the personal agents might inhabit in the same machine. This is the case of our system: 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 (see Figure 2).



(a) Main menu.

(b) Feedback menu.

(c) User context settings.

(d) Selective attention filters.

Figure 2: iPOIs interface.

The `Master Agent` is responsible for starting, not only the Web Agents, but also the Personal Assistant Agents (PAAs), described in Figure 4 as $\texttt{PAA}_1 \cdots \texttt{PAA}_n$. The `Master Agent` is also responsible to reply the `PAAs` when they ask for information about a specific POI. Although the system is capable of retrieving POIs' 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), for the purpose of this work only the Foursquare service is used, which explains why in this work we used only one Web Agent ($\texttt{WA}_{\texttt{foursquare}}$). As it can be seen in Figure 2a, the system shows all the POIs retrieved from the system, taking into account the current user's context and intention (Figure 3), as well as his/her selective attention preferences (Figure 2d). Clicking in each POI's icon, the user can see an information window with the expected surprise and information gain values associated to the price, schedule and day(s) off. One of the most relevant feature of this interface is the menu presented in Figure 2b, where the user is allowed to give feedback about the expectations of his PAA.

$\texttt{WA}_{\texttt{foursquare}}$ implements several methods available through the Foursquare API[3], allowing it to start requesting for POIs in a pre-defined geographical area. During this process, it filters out all the POIs that do not belong to the categories of concern, and stores the remaining POIs in the system's database (presented in Figure 4 as `POIs Database`). This autonomous agent is constantly searching for new information, and verifying if the data stored in the database is up-to-date.

Context is the key to personalise recommendations made by the PAAs for their users. Thus, a set of attributes need to be defined in order to characterise the `POI`'s context, as well as the `user`'s context and intentions. Since these attributes need to be combined, an Android application, named iPOIs, was been created to this purpose, i.e., to show the current user location, his context and intention. The main attributes used to define the user, the POI and the information available in the interface are shown in Figure 3.

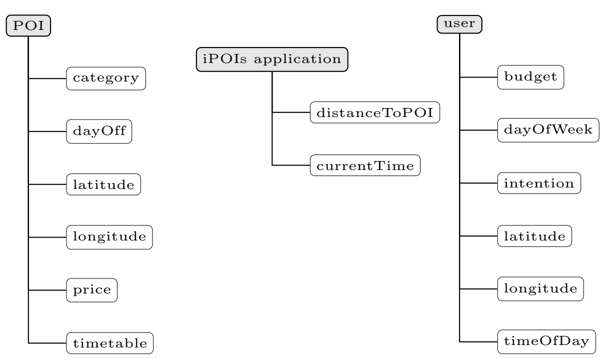


Figure 3: Main attributes used to define the context of the user, POI and the iPOIs application.

Possible values for each attribute of the `POI`'s context are:

- `category = {food, shopping, nightlife}`, actually we use the `sub-category, e.g., food =` $\langle$`sandwichShop, vegetarian, etc.`$\rangle$`, shopping =` $\langle$`men'sApparel, women'sApparel, etc.`$\rangle$ `and nightlife =` $\langle$`wineBar, disco, etc.`$\rangle$
- `dayOff = {a day of the week or combinations}`

[1]https://developer.foursquare.com/
[2]http://msdn.microsoft.com/en-us/library/hh441725
[3]`https://developer.foursquare.com`

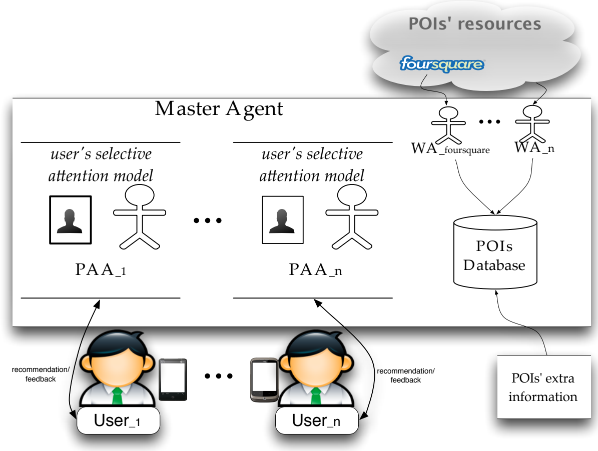


Figure 4: System's Architecture.

- `price = {cheap, average, expensive}, e.g., for lunch {cheap`$\leq$`5€; 5€>average`$\leq$`7€; expensive>7€}`
- `timetable = {morning, afternoon, night, or combinations}`

Possible values provided by the `iPOIs interface` are:

- `distanceToPOI = {near`$\leq$ $200m$`;` $200m$ `>average`$\leq$ $300m$`; far>` $300m$`}`
- `currentTime = {current day of the week and period of the day (morning, afternoon or night)}`

Possible values for each attribute of the `user`'s context are:

- `budget = {low, medium, high}, e.g., for lunch {low`$\leq$`5€; 5€>medium`$\leq$`7€; high>7€}`
- `dayOfWeek = {current day of the week}`
- `intention = {coffee, lunch, dinner, party}, e.g., drink coffee in a {bakery, coffeeShop, etc.}, have lunch and dinner in {burgers, BBQ, etc.} and party in a {bar, disco, etc.}`
- `timeOfDay = {morning, afternoon or night}`

Let us illustrate how the value of information is computed by the selective attention mechanism. Suppose that a traveller's navigation system provided the information of a specific POI, a restaurant denoted by A, for an agent (that represents a driver) based on its profile (e.g., preference for cheap restaurants). Suppose the agent has the following expectations for the price of POI A, for a certain period/time of the day for a certain day of the week: 60% of probability of "low price" (event E_1), 30% of probability of "moderate price" (event E_2), and 10% of probability of "high price" (event E_3). Suppose the desire strengths of these events are 1, -0.5, and -1, respectively. What is the relevance of becoming aware that the price of restaurant A is low (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:

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

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

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

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.

By filtering out information that seems to be uninteresting, the selective attention mechanism prevents an agent (and also its owner – a driver in this case) from being interrupted so many times as in the absence of the selective attention mechanism and consequently prevents its reasoning/decision-making resources from dealing with irrelevant information. But, is the quality of the decisions of the driver affected by not receiving that presumably irrelevant information? In other words, was the suppressed information erroneously considered as irrelevant? If the answer is "yes", we have a false negative. This error occurs when we are making a negative inference which is actually true. In the above example, if the information of the occurrence of E_3 was not revealed, the driver would have stopped and enter restaurant A that might be less useful than an alternative. The reverse can also happen: was the provided information erroneously considered as relevant? If the answer is "yes", we have a false positive or false alarm. This error occurs when we are making a positive inference which is actually false. This problem of knowing the correctness of preventing an interruption is quite similar to errors type I and II of statistical hypothesis testing. A reasonable empirical way to answer these questions is by comparing the classifications of the selective attention agent to those of humans. This is the main goal of the experiment described in the next section.

4. EXPERIMENT

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, 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 experimentation was performed in downtown of the city of Coimbra, Portugal, which is characterized by a high density and diversity of POIs. Furthermore, the type of POIs considered were restricted to `{Food, Shopping, Nightlife}` which are among the more frequent categories in that region of the city. The number of sub-categories for `Food` are `44`, `Shopping 8` and `Nightlife 11`, with `271`, `10` and `84` different POIs, respectively. The extra information manually gathered from these `365` places was the POI's price, the day off and the timetable.

This experiment can be divided into three different evaluations. Firstly we made a manual evaluation, to analyse the true relevance of the recommended POIs, and calculated the exact agreement between the human judges. Then, we performed a correlation analysis to compare the selective attention values given by the PAAs with those of the manual evaluation. Finally, we analysed the system performance.

To test our approach, we used a set of real scenarios. More precisely, in this experiment we used three different locations with higher POIs density. The information of these different locations was combined with different situations (i.e., different user's contexts and intentions). Each one of these combinations is called a *run*. For instance, r_1 = `[40.208934, -8.429067, Morning, Sunday, Coffee]` represents one of those runs in which it can be seen the user's GPS location, time of day, day of the week and intention/goal. In this experiment, we analysed 13 runs in a total of 65 evaluated POIs[4]:

- 5 runs, goal: drink a coffee (25 evaluated POIs);
- 2 runs, goal: have lunch (10 evaluated POIs);
- 3 runs, goal: have dinner (15 evaluated POIs);
- 3 runs, goal: go party (15 evaluated POIs).

To perform this evaluation, we used the interface of the iPOIs application, illustrated in Figure 2.

We asked 9 human judges to rate some POIs attributes about the surprise and uncertainty-based value. The attributes evaluated in the experiment were the POI's price, the POI's schedule, the POI's day(s) off and the POI as a whole. Each human judge was asked to assign one value to these attributes, considering their information gain and surprise, using the scale $\emptyset$ to 5, where $\emptyset$ means that there was no information gain (regarding its uncertainty-based value) or no surprise (regarding the surprise intensity). We then calculated the exact agreement (`EA`) between the human judges used to calculate the coefficient correlation with the values of surprise and information gain computed by the artificial agents.

The `EA` among the judges (`EA`: $0\% \leq$ `EA` $\leq 100\%$), for all the data evaluated, is presented in Table 1, where the attributes price, schedule, day(s) off and all the attributes together are presented as `Price`, `Sche.`, `D.Off` and `All`, respectively.

Table 1: Exact agreement between the human judges.

Information gain				Surprise			
Price	Sche.	D.Off	All	Price	Sche.	D.Off	All
100	98.58	97.61	100	100	97.61	96.64	100

The parallelism between the exact agreement of humans

[4]This evaluation, in average, took approximately 1 hour.

and the uncertainty and surprise-based values computed by the artificial agent about the POIs' attributes was quantified by Spearman's coefficient. This correlation coefficient give us an idea on how these variables are correlated.

Table 2 shows these correlation coefficients between the EA, given by the human judges, and the uncertainty and surprise-based values computed by the artificial agent for the four types of attributes considered, through the 13 runs. As it can be seen, the results are promising. Although this means that there exists a positive correlation in general, some of them do not have a strong correlation value (for instance, the surprise value for the POI's attribute price). This happens due the fact that the price was not so surprising to the judges than the day(s) off. For example, when the agent presents similar surprise expectation values to cheap and average and the POI's price is cheap, the judges do not gave a high surprising value to this information. On the other hand, the judges gave a high surprise value when the POI is closed and the agent presents a low surprise value to that specific day(s) off. The opposite occurs to the importance that the judges gave to the uncertainty-based value of the price.

Table 2: Correlation between the EA and the selective attention models.

Information gain				Surprise			
Price	**Sche.**	**D.Off**	**All**	**Price**	**Sche.**	**D.Off**	**All**
0.8459	0.4036	0.4218	0.6321	0.2557	0.5811	0.5218	0.4901

Finally, in the third part of the experiment, we performed an information retrieval task, where the uncertainty and the surprise components (named α and β, respectively) was used to analyse the system's performance. To do that, we used the α's and β's average (i.e., $\overline{\alpha}$ and $\overline{\beta}$), from the 13 runs, for the four POI's attributes analysed in this work. To measure the quality and the quantity of POIs correctly selected, precision, recall and F_1 were computed in the following manner:

$$Precision = \frac{Selected\_correct\_POIs}{Selected\_POIs} \tag{8}$$

$$Recall = \frac{Selected\_correct\_POIs}{Total\_correct\_POIs} \tag{9}$$

$$F_1 = \frac{2 * Precision * Recall}{Precision + Recall} \tag{10}$$

For each component, Table 3 presents the resulting precision, recall and F_1 scores (expression 8, 9 and 10) and the respective α's and β's used, where the attributes price, schedule, day(s) off and all the attributes together are presented as Price, Sche., D.Off and All, respectively.

As it can be seen, the selective attention components performed similarly regarding the distinct attributes. Nevertheless, the F_1, on average, for the α component is higher than the F_1 average for the β ($\approx$74.90% and $\approx$62.36%, respectively), which means that the uncertainty-based component performs better than the surprise component on average. Even though some of the F_1 values show low performance (e.g., the attribute price with β=0.9542 (34.78%)), most of them achieve high F_1 (e.g., the attribute price with the α=0.0625 (93.75%) or the attribute schedule with the β=0.9180 (81.97%)). These results are promising,

Table 3: System's performance for the two selective attention components, with their respective α and β.

		Precision (%)	**Recall (%)**	F_1 **(%)**
Price	α=0.0625	90.90	96.68	93.75
	β=0.9542	24.24	61.54	34.78
Sche.	α=0.0975	93.93	52.54	67.39
	β=0.9180	75.75	89.29	81.97
D.Off	α=0.0469	96.97	55.17	70.33
	β=0.9342	60.61	83.33	70.18
All	α=0.0646	93.94	53.45	68.13
	β=0.9429	45.45	100	62.50

supporting the idea of applying a computation model of selective attention into location-based services, as an alternative or an extension of traditional recommender systems.

5. CONCLUSIONS

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).

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. This may be of high value in critical situations such as driving a car in that, as reported by [8], numerous cognitive studies have provided evidence of the problems in information processing exhibited by humans when dealing with large amounts of information such as that the speed at which humans perform tasks drops as the quantity of information being considered increases, and that the rate of performing tasks can be increased by filtering irrelevant information.

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