Acquiring Unobtrusive Relevance Feedback through Eye-Tracking in Ambient Recommender Systems

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Abstract. Acquiring relevant information to keep user's preferences up-to-date is crucial in recommender systems in order to close the cycle of recommendations. Ambient Intelligence is a suitable approach for non-intrusively closing the loop in recommender systems using ambient eye-trackers. We combine a method for acquiring relevance feedback through eye-tracking with the functionalities of an extractor agent. We describe the results of experiments conducted in a recommender system to obtain implicit feedback using eye fixations. Finally, we obtain a ranking of user's most relevant preferences and behaviours.

Keywords. User Modelling, Ambient Recommender Systems, Implicit Relevance Feedback, Eye-Tracking

1. Introduction

An Ambient Recommender System pro-actively operates as a *surrounding intelligent adviser* on the behalf of the users in an everyday context [13]. Their added value is based on their ability to unobtrusively give suitable advice, recommendations, or predictions that are of interest to each user in his/her particular context. Learning user preferences in Ambient Recommender Systems is a complex task which depends on automatically evaluating both successful (i.e. positive) and unsuccessful (i.e. negative) recommendations for the user. This evaluation is obtained through feedback given by the user to the system.

Usually, users provide recommender systems with little information they can use to *close the loop* in recommendation processes. Therefore, recommender systems do not have enough data for evaluating the positive and negative recommendations suggested to users. In addition, several machine learning techniques do not have high performance and in some cases they cannot be applied. In parallel, these techniques are converted into supervised and unsupervised learning techniques as a collateral effect. Therefore, the automatic evaluation of recommender systems cannot be performed by any of them in an isolated way.

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One solution for reducing unknown recommendations is to improve implicit relevance feedback acquisition through embedded ambient devices like eye-trackers. In this paper we research implicit feedback in recommender systems using eye-tracking in order to extend the binary data (i.e. positive and negative recommendations) of relevance feedback into a ranking of preferences. Implicit feedback means that the system automatically infers the relevance information in order to update the user model from the user behaviour.

This paper is organized as follows: Related work on eye-tracking in several research areas is introduced in the next section. Section 3 defines the unobtrusive relevance feedback. Then, the acquisition of relevance feedback in an Ambient Recommender system is analyzed. In section 5, experimental results are examined. Lastly, we present some conclusions and future work.

2. Related work

Eye-tracking is a technique which allows eye movement and eye-fixation patterns of a person to be determined. Eye-tracking research has its genesis in psychology [12]. Several variables of ocular movements such as rapid eye movements, *saccades*, eye fixations, *gaze time* and pupil dilation among others have been measured in order to explain user behaviours in several application domains. For instance, in user modelling research several studies of user behaviour have been analyzed in the Information Retrieval domain [6], and learning environments [2]. In Human-Computer Interaction, eye-tracking has been used mainly to improve website designs and increase their usability [11].

However, acquiring relevance feedback through eye-tracking in open environments such as Ambient Recommender Systems is a promising and unexplored research area that we address in this paper. This paper is part of an ongoing research work concerned with developing an adaptive user model [3,4,5], which requires a mechanism for acquiring relevance feedback in order to give more accurate recommendations to its user.

3. Unobtrusive relevance feedback

Unobtrusive relevance feedback concerns with the transparent and unnoticeable way in which the inputs are acquired by the system. The information required by the recommender system is obtained by natural interaction without annoying the user.

Acquisition of relevance information to keep the user model up-to-date in Ambient Recommender Systems involves several approaches in order to obtain both positive and negative evaluations of recommendations [10,14,8]. This information is called *Relevance Feedback* [9]. Generally, feedback about the recommended items can be classified into two classes: positive feedback and negative feedback. In the first case, the user assesses explicitly or implicitly the items he/she likes. In the second case, the user assesses explicitly or implicitly the items he/she dislikes.

The research presented here seeks to determine if the information displayed by the recommender system once it has delivered recommendations is what the user likes or dislikes, (i.e. interests and preferences) while taking into account that there is a range of recommendations that could be between these two possible extremes. These perceptions

Not at All	Not	Not Much	Normal	A Little Bit	Quite a Lot	Very Much
(0, 0.14)	(0.14, 0.28)	(0.28, 0.42)	(0.42, 0.57)	(0.57, 0.78)	(0.71, 0.85)	(0.85, 1)

Figure 1. Normalized Semantic Scale of Relevance Feedback

are quite different in each user and it is necessary to classify them in order to obtain more accurate relevance feedback . A semantic differential method for these values is assumed in this research as is described in [4]. See figure 1.

4. Acquiring unobtrusive relevance feedback

Very large and high-dimensional data sets produced by Ambient Recommender Systems and several kinds of data sources for user modelling (among others, weblogs, socio-demographic databases, transactional databases, preference and attribute databases, and sensory databases of eye-tracking), can be pre-processed efficiently with our *Extractor Application Agent*. We have configured a method for measuring these variables in our experiment as we explain in this section.

4.1. Acquiring measures of ocular movements by applying an extractor agent

In this study several variables of eye movements have been analyzed. We focused on *gaze time* as the most accurate unobtrusive variable measured by eye-tracker devices. By definition eye-fixation takes between 200 and 300 milliseconds [7]. We consider eye-fixation as a source of relevant information about user preferences once the recommender system delivers its recommended items given that the user's attention is directed at a specific area of displayed information.

The eye movements of users are tracked by an Tobii 1750 eye-tracker embedded in a 17" TFT monitor. This makes the eye-tracking components nearly invisible to the users and facilitates a much more comfortable and unobtrusive environment.

Broadly speaking, our approach for dealing with any type of objective, subjective or emotional user feature, whether explicit (i.e. socio-demographic data and transactional data) and/or implicit (i.e. web usage data and sensory data) and from several application domains is termed *Multi-agent Smart User Model (MASUM)* [5]. For this purpose, we use the multi-agent architecture described in [3]. In this paper we focus on using this kind of Multi-agent Smart User Model in Ambient Recommender Systems in order to obtain the relevance feedback for recommendations unobtrusively. The multi-agent system has been deployed for operating in a distributed environment and it can acquire the user model from several sources as shown in Figure 2. A suitable functionality of our multi-agent system is the *Extractor Application Agent* which can preprocess the user lifelogs[1], extracting several variables, such as fixation order, gaze time, average fixation duration, fixation count, time to first fixation, among others, in different data formats. This agent delivers a clean and preprocessed user lifelog in order to establish a user model from raw data sources.

[1] A user lifelog is a complex set of raw data of all user activities in Ambient Intelligence applications, i.e. socio-demographic data, web usage data, sensory and ambient data, attributes databases, transactional data, etc.

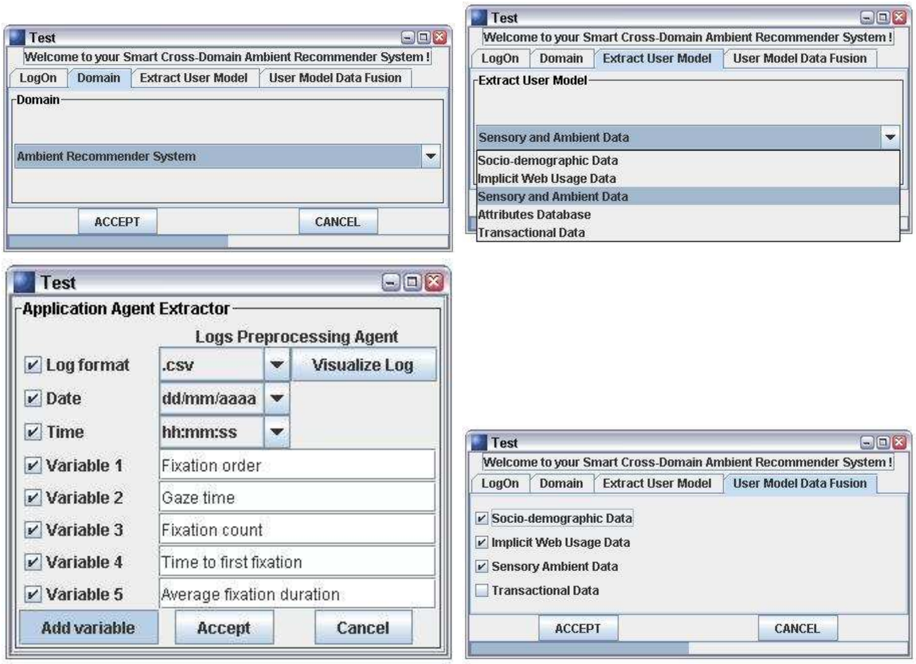


Figure 2. Multi-agent Smart User Model: Extractor Application Agent from sensory and ambient data sources.

Once the *MASUM* has extracted the information from ambient applications we can analyze the relations between user models and relevance feedback obtained from eye-tracking as described in the next method.

4.2. Method for acquiring relevance feedback through eye-tracking

In our study we have collected data from 40 users of a restaurant recommender system. Each user has his/her own user model for the restaurant recommender system and his/her preferences are stored in his/her lifelog. We grouped the users into four groups to facilitate eye-tracking tests.

In our tests, we divided the display area of the restaurant recommender system into several zones. In particular, we defined three special zones, namely: *register*, *advanced search* and *recommendations*. These zones allow us to acquire gaze points, fixations, scan-paths and hotspots in order to determine values for these three groups of variables. We consider that a user is interested in a recommended item when his/her mean gaze time and the time of first fixation exceed 300 milliseconds in the recommendations zone. The extra average time taken in each zone indicates the degree of interest in the recommendations. Therefore, we have tuples of users, average gaze time of the user, time spent on recommended items, time to first fixation of the user, item recommended. For instance, if a user spends a longer gaze time on a restaurant suggested by the recommender system to the average time spent on other restaurants, our method assigns a weight directly proportional to the additional time spent on the fixation of this recommended item. In this way we can measure the acceptance or rejection of a user of a set of suggested items.

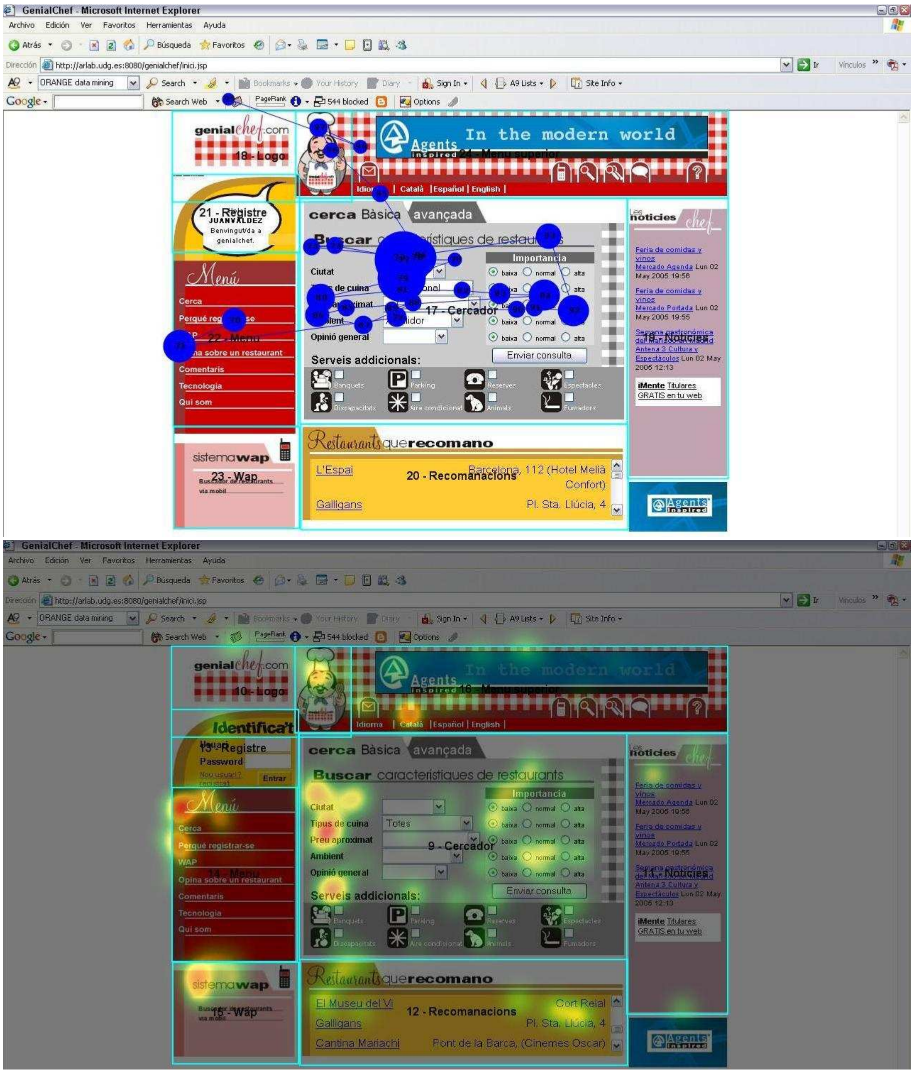


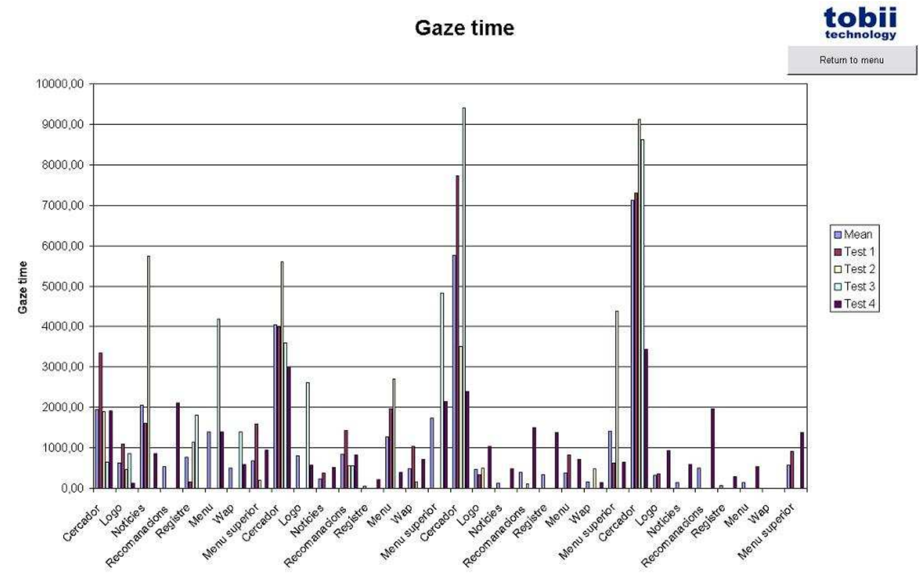
Figure 3. Initial plot displaying gaze points, fixation, scan-paths and hotspot gaze visualization of eye-tracking test sessions in a restaurant recommender system

Then, we establish a ranking for each tuple formed by the items recommended to a user, sorted by their assigned weight.

Each user had to login in the restaurant recommender system and then he/she had to do a search in the *advanced search* zone of the application. Once the results were shown an extra time of 10 minutes was given to explore the system. See figure 3.

4.3. Experimental results

The results obtained from applying our method show that the average gaze time spent on visualizing recommended items for each user is superior to a gaze time of 300 mil-



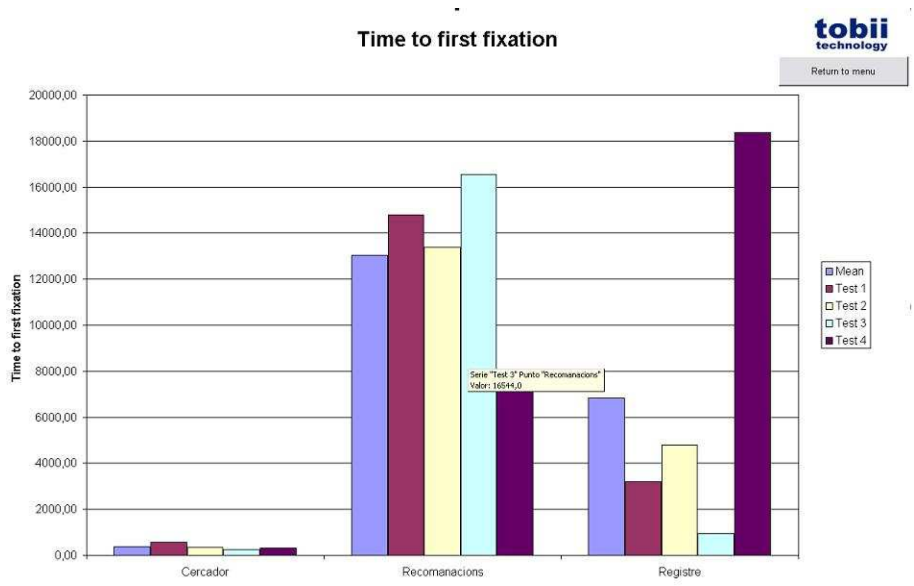
	Min	Max	Sum	Mean	Median	Test 1	Test 2	Test 3	Test 4
1 Cercador	10742	22366	75499	18874,75	21195,5	22366,0	20125,0	22266,0	10742,0
4 Recomanacions	558	6399	9051	2262,75	1047,0	1436,0	658,0	558,0	6399,0
5 Registre	159	1872	4981	1245,25	1475,0	159,0	1137,0	1813,0	1872,0

Figure 4. Gaze time spent on each display zone of restaurants recommender system and Gaze time spent on recommended items

liseconds as shown Figure 4. This experiment allows us to obtain the ranking made up of all restaurants recommended by the system in which each user has been interested (i.e he/she spent more than 300 milliseconds). In addition, weights are given by the arithmetic difference between gaze time and average gaze time spent for each user in each tuple of recommended items. In this manner, we confirmed that he/she could be interested in the restaurants visualized on each information display in the recommendation zone, because the time is quite different for each item. Even though, we have focused on the gaze time, we can see in Figure 5 that the time to first fixation for the same items is large compared with the average gaze time of each user. This means that the recommender system interface could be improved in terms of usability.

5. Conclusions and future work

In this paper we introduce an innovative framework and mechanism for improving the automatic evaluation and acquisition of unobtrusive relevance feedback in Ambient Recommender Systems. We have integrated eye-tracking with an *Extractor Application Agent* in order to acquire the relevance feedback in an unobtrusive way and keep the Smart User Model up-to-date. Different eye-tracking variables have been extracted and analyzed with the Extractor Application Agent. However, this agent can efficiently preprocess complex sets of raw data in ambient applications (i.e user's actions) in order to



	Min	Max	Sum	Mean	Median	Test 1	Test 2	Test 3	Test 4
1 Cercador	255	549	1450	362,50	323,0	549,0	336,0	255,0	310,0
4 Recomanacions	7368	16544	52111	13027,75	14099,5	14804,0	13395,0	16544,0	7368,0
5 Registre	953	18373	27309	6827,25	3991,5	3201,0	4782,0	953,0	18373,0

Figure 5. Time spent in first fixation and time spent in first fixation of recommended items in a recommender system

acquire a better understanding of the user's preferences. We focused on analyzing the length of the gaze time as the best indicator of the user's cognitive process. The framework proposed was tested in a restaurant recommender system, but it can be applied to several domains.

Our next step is to complete our approach by integrating this mechanism to acquire relevance feedback in a K-SVCR Multi-classifier [1] in order to automatically generate a ranking of interesting items for each user in real-time.

Finally, we would like to stress that eye-tracking is a suitable way of acquiring user feedback. However, designing experiments using this technology implies inherent privacy issues at present. We assume that this technology will be used increasingly in the next generation of Ambient Recommender Systems.

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