EVALUATION OF ATTENTION PROFILES

LIS 678 Personalized Information Delivery

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Abstract

This paper presents a research proposal for an evaluation study of attention profiling, a form of user modeling that captures a person's attention on the Internet. Our proposal explores two options for the study: 1) profiling users' web browsing behaviors; 2) profiling online music listeners' taste. The first option is a qualitative case study of a small group of users of Cluztr, a Firefox browser plugin. The second option is a quantitative, cross-sectional study of a larger group of users of Pandora, an online music recommender. Both options involve an evaluation of relevancy and accuracy of the recommendations provided by each respective service. Our objective is to investigate whether attention profiling accurately matches people's interests and information needs. We will also examine factors that impact the accuracy of attention profiles. The outcome of this research could lead to the adoption of attention profiling in services that provide information retrieval (IR) and information filtering (IF).

Keywords

Attention Profiling, Attention Metadata, User Modeling, Information Retrieval, Information Filtering, Portability, Privacy, Context.

1. Introduction

Modeling a person's attention not only capture the *what*, but also the *how*, *when*, *to which end*, and *for how long* a person interacts with a particular resource (Roda & Nabeth, 2007). Vuorikari (2008) describes attention data as "capturing and taking advantage of users' interactions with the content (e.g. downloading, buying, listening, reading feeds) and users' reactions to that content (e.g. ratings, reviews, tags)". The result is a collection of a person's interests and values derived from his or her interactions with different digital systems on the Internet. By combining what each system learns about the same person, attention profiling creates a richer and more accurate model of the person's aims and goals (Wolpers et al., 2007).

The concept of attention profiling have drawn researchers from both the academic and commercial worlds. In academia, the largest effort to date has been coordinated by a group of researchers in Europe. Wolpers et al. (2007) proposed a framework and schema called Contextualized Attention Metadata (CAM) to capture students' and teachers' interactions with digital content in learning environments. On the other hand, Chris Saad, founder of Faraday Media (http://www.faradaymedia.com), proposed an open specification called Attention Profiling Markup Language (APML). Since then, several Web 2.0-styled websites have adopted APML as the primary vehicle for profiling user characteristics. In spite of these efforts, majority of these researches focus on the capture and management of attention profiles; while little is known about the validity of these attention profiles. Additional research in evaluation of attention profiles could lead to more accurate modeling of user behaviors which could be beneficial for information retrieval (IR) and information filtering (IF) services.

2. Background

Vast amount of literature has been dedicated to research of ways to combat information overload. Information overload refers to "the state of having too much information to make a decision or remained informed about a topic" (Toffler, 1970). Imagine the days when your e-mail inbox is filled with messages that require your attention, or a news site updating its articles on your favorite subject on a minute-by-minute basis. With the explosive growth of information on the Internet, this problem is only worsening. Over the years, researchers from a wide variety of disciplines have made strides in improving both IR and IF. Many of these improvements are ubiquitous in our daily lives: Google search engine (IR), YAHOO! directory (IR), Amazon's "Users who have bought this book also bought..." feature (IF), and Netflix's movie recommendation engine (IF).

Services that provide IR or IF rely on accurate modeling of both users and content. A user model is a system's assumptions about a user that includes his or her information needs and preferences (Quiroga et al., 2004). A user profile is a form of user modeling. It contains information that are relatively static such as a person's name, gender, race, occupation; while other information that are more dynamic such as a person's current needs, interests, likes, and dislikes. Content modeling, on the other hand, is an abstract representation of a piece of information. An example of such representation is a description of an auction item on eBay. The majority of IR and IF services focus on a mapping between user and content modeling to reduce information overload.

2.1 Attention Profiling: an Overview

Attention profiling is a holistic approach of user modeling. The concept is founded on the idea that behavioral patterns can be derived from what people pay attention to. Unlike filtering services (e.g. recommenders, alerting) that are offered within a single system, attention profiling captures "user actions across system boundaries to enable better targeted personalization" (Najjar et al., 2006). Consider the following scenario:

you enjoy listening to music from an online radio service while studying for your nursing entrance exam. One day, you visit your favorite online shopping website to shop for a birthday present for your friend. Upon arriving at the website, you are presented with a list of CDs that you may be interested in, ranked according to listening profile from the online radio service. This type of integrated service is closer than what many people believe. The enabler is a framework to accurately capture and interpret what people pay attention to in a holistic manner.

The knowledge of what people pay attention to is valuable to content providers. Davenport and Beck defines human attention as the new "valuable currency" (Davenport & Beck, 2001); while Goldhaber describes attention as "intrinsically, unavoidably scarce" (Goldhaber, 1997). Goldhaber further contrasts the difference between the money-based economy that relies on tangible goods and the new attention economy. The growth of the World Wide Web is one aspect of the transition from money-based economy to attention economy. With this continuous growth, capturing attention data is the first but important step to understand people's information needs.

2.2 Capturing Attention Data

Attention data can be captured at four different levels: physical, psycho-physiological, application, and user-directed (Roda & Nabeth, 2007; Vertegaal, 2002).

Physical observations include monitoring of key strokes, mouse gestures, and tracking of eye movements. Vertegaal identifies some of the fundamental problems with attentive interfaces that utilizes eye-tracking (Vertegaal, 2002). First, most eye-tracking devices are intrusive which has an impact on a user's normal behavior. Secondly, interpretation of the attention data can be problematic. A long and intense gaze at a specific area of a screen can possibly mean confusion or interest. Furthermore, it is difficult to derive a user's interest and behavior pattern from the enormous amount of data (Wolpers et al., 2007).

Psycho-physiological data includes a person's heart rate, blood pressure, temperature, and etc. Similar to physical observations, capturing psycho-physiological data is intrusive and is difficult to achieve beyond a laboratory environment.

Application-level monitoring is by far the most common form of capturing attention data. Information need can be derived from users' interactions with digital information in various Internet activities (e.g. web browsing, e-mail, instant messaging). Wolpers et al. propose a schema and framework called Contextualized Attention Metadata (CAM) that enables the collection and management of attention data from various applications (Wolpers et al., 2007). These applications include Mozilla Firefox browser, Microsoft PowerPoint, MSN Messenger, and Winamp music player. The detail of CAM will be discussed in Section 2.5.

User-directed input is data explicitly specified by users about their current states and needs (Roda & Nabeth, 2007). Although this information is valuable because of its accuracy, the act of providing this information ultimately distracts the users from their current tasks.

The remainder of this paper will focus primarily on attention profiling at the application level.

2.3 Interpreting Attention Data

Making sense of attention data is the second step towards building a user model based on people's attention. After attention data is captured from various Internet activities, it is up to each individual application and service to interpret the attention data and derive usage behavioral patterns from them. Wolpers el al. (2007) have extensively studied the collection and management of attention metadata in learning environments using the CAM framework and schema. By building relations among different actions (e.g. searching for course material, requesting access to a specific document) from students and teachers, assumptions about people's characteristics can be made. For instance, if a teacher repeatedly creates digital resources in a particular topic, one can assume that he or she is an expert in that area.

Understanding what people pay attention to is most beneficial to IF systems such as recommenders (Najjar et al., 2006; Ochoa & Duval, 2006; Wolpers et al., 2006). A user profile built on attention data allows recommenders to identify resources that a person is most likely interested in based on previous interactions. Ochoa and Duval (2006) proposed four ranking and recommending metrics in Learning Management Systems (LMS): link analysis based ranking, similarity metrics for recommendation, personalized ranking, and contextual recommending. All of which rely on capturing and interpreting users' actions (e.g. creating learning objects, searching for relevant objects) in various learning environments.

2.4 Properties of Attention Data

To understand attention profiling broadly, it is important to look at some of its issues:

Portability is one of the primary selling points of attention profiling. In traditional user modeling, each application and service stores the profiles of their users in a way that is difficult to integrate together. For instance, a person's shopping histories and preferences on Amazon and eBay cannot be easily combined. A combined profile containing a user's attention data can be valuable. Such profile is the perfect source for recommenders because it provides a history of user interactions in a holistic manner (Wolpers et al., 2006). On the other hand, millions of Internet users are engaging in social networking activities on Web 2.0 sites like Facebook and MySpace nowadays. People are more willing to provide private and identity-related information on the web (e.g. what you are currently doing on Twitter). A move to make these social data portable is crucial to the continuous success of these social networking sites (Heyman, 2008). A number of frameworks and schemas have been proposed over the past few years to make attention data portable: AttentionXML, Contextualized Attention Metadata (CAM), and Attention Profiling Markup Language (APML). However, none of these have emerged as the de-facto standard for user modeling.

Privacy is an issue related to portability. One may argue that a person's privacy may be in jeopardy if he or she is constantly being monitored on what he or she pays attention to. However, the opposite may be true. One of the philosophies of AttentionTrust (http://www.attentiontrust.org), a non-profit organization, is to empower users to take control of their own attention data (AttentionTrust, 2008). With attention profiling, it becomes transparent to the users on what is being captured and how it is being utilized. It is up to the users to determine whether a specific system should have access to their attention data. For instance, Engagd (http://www.engagd.com) is a framework that utilizes the OpenID technology to allow application developers to store and access people's attention data in APML format.

Context is an issue that has been studied extensively in user modeling. Quiroga and Mostafa (2002) showed the role of context in users' relevance feedbacks in IF systems. Their study explained that the low performance of IF systems was a result that user profiles were solely based on topics and disregard the role of context. Examples of non-topical characteristics that they found include domain expertise, credibility of information source, comprehensibility and approach. Wolpers (2008) also pointed out the importance of context in a digital learning environment. The context in which learners operate in must be captured during their information gathering process. For instance, if a learner is researching for a particular topic, it is beneficial to understand contextual information such as the course that the learner is researching for, how long the research project is, or even what the learner's motivations are. While this might be difficult to achieve within a single system, it is entirely possible if user-driven activities can be captured to induce the learners' information needs.

2.5 Current Frameworks and Schemas of Attention Profiling

AttentionXML is an open specification introduced in 2004 by Steve Gillmore, the president of AttentionTrust. It is the first known schema for capturing attention metadata. Figure 1 below shows the various elements of the AttentionXML schema. The Attention Metadata Management (AMM) framework demonstrates the use of AttentionXML to track learning objects that people pay attention to (Najjar et al., 2005). The framework captures user interactions with various tools including web browsers, e-mail clients, audio/video players, and messaging system. The resulting data from each tool are then combined to form a single AttentionXML file for each user.

Blog / Feed / Site	Post / Item / Page
• Title • URL • Alt URL • Etag • Last Updated • Date Added • Date Removed • Last Read • Read Times • User Title • Rel / xfn • Rel / Vote Link • Tags	• Name / Title • Guid / Identifier • Type (MIME Type) • Etag • Last Updated • Last Read • Duration • Followed Links • Rel / Vote Link • Tags

Figure 1 AttentionXML Schema

Contextualized Attention Metadata (CAM) is an extension to the AttentionXML schema (Najjar et al., 2006; Ochoa & Duval, 2006; Wolpers et al., 2006; Wolpers et al., 2007). The most recent schema, released on April 3, 2007, can be found at: http://ariadne.cs.kuleuven.be/empirical/attention.php. Similar to AttentionXML, CAM primarily focuses on capturing user interactions in learning environments including Learning Object Repositories (LOR), Learning Management Systems (LMS), and authoring tools (e.g. Microsoft Office applications). CAM was designed to overcome the shortfalls of AttentionXML by capturing user activities (e.g. searching, editing, downloading) from various applications. The addition of the *event* element in the schema allows capturing of various activities at the individual item level. This is considered a resource-centered approach (Roda & Nabeth, 2007). Based on these captured activities, a teacher, for example, can determine the amount of time students spent on a document, interest level and usefulness of certain category of documents, and social relationships among documents.

Attention Profiling Markup Language (APML) is a schema for storing a person's attention metadata. It is maintained by the APML Workgroup, currently led by Chris Saad. The specification and schema can be found at: http://apml.pbwiki.com/. APML deals with people's attention on an abstract level. It organizes people's attention and interests into *concept* elements, which have their respective *value* attributes. The *value* attribute, ranges from -1 to +1, indicates degree of confidence in which an application has determined. While both AttentionXML and CAM focus on the capture and management of attention metadata, several APML-enabled services utilize attention profiles as a source for information filtering and recommendations. For instance, Cluztr (http://www.cluztr.com) is a plugin for the Firefox browser which captures websites that users visit and provide recommendations to related websites accordingly. Each user profile, in the form of an APML file, provides patterns of a user's browsing behavior.

4. Research Objectives

The purpose of this research study is to measure the accuracy of attention profiles. In all of the related work thus far, the focus has been on the development of a framework to effectively capture attention metadata from different environments. Little has been done to evaluate the validity of these attention profiles. In addition, we will examine the different factors that impact the accuracy of these profiles.

5. Study Design

Two options for the design of this research study are being considered. Due to the time constraint in this class, we are still undecided on which of the options to proceed. We will present below an overview of each of these options along with its respective methodology, sampling strategy, strengths, and weaknesses.

5.1 Option 1: Case Study

The first option involves monitoring of research subjects' web browsing behavior in a 3-month period. A Firefox browser plugin called Cluztr (http://www.cluztr.com) will be installed on each subject's computer. The contents of the websites that each subject visit are captured and analyzed to generate an APML file, which is stored on a remote server. For privacy reason, Cluztr automatically disregards any secured websites (i.e. any websites with URLs that begin with https://). Subjects also have the option to add specific URLs to their private lists so that these websites will not be added to their profiles. Furthermore, subjects can remove any URLs from their profiles once they have been captured. After an APML file has been generated based on a subject's browsing taste, the Cluztr plugin continuously provides a list of recommended websites whenever the subject visits a webpage. The subject can at any time click on one of these recommendations.

Data will be collected from research subjects through in-person interview sessions at the end of the 1st, 2nd, and 3rd month of the study. Each interview session will take approximately 30 minutes, and will consist of mostly open-ended questions. These questions will motivate the research subjects to discuss issues and challenges that they have encountered, examples of recommendations that match and do not match their interests. Research subjects may also be asked during the interview to demonstrate a browsing session to show examples of recommendations. As the research progresses, research subjects can indicate any improvements in regards to the recommendations provided by Cluztr.

We intend to evaluate the accuracy of attention profiling from the recommendations that Cluztr generate. Web browsing is an experience that cannot be rated in a quantitative manner. Therefore, we decided not to approach the research study with surveys or questionnaires with Likert-scaled questions. In addition, direct observations will be avoided because research subjects will likely detract from their normal behaviors with the presence of observer(s). Instead, an in-depth examination of a few cases through periodic interviews will allow us to collect “personal” responses that would not be possible in a quantitative study. From this analysis, we can generalize whether attention profiling creates an accurate model of the users.

We will employ a purposive sampling strategy in this research study. Between 1 to 3 people will be recruited for this research. We anticipate that certain potential recruits may refrain from participating because of the fact that their browsing activities will be monitored. Therefore, we will target our recruitment effort towards college undergraduates or graduates who browse the web primarily for academic purposes. The research study will last for 3 months in which each research subject will be interviewed once a month.

An advantage with this research study is that it covers all aspects of the subjects' web browsing behavior. Instead of monitoring within a specific domain (e.g. music), Cluztr captures attention from all websites that the subjects visit. It can potentially provide maximum impacts and benefits for research subjects since it will have more opportunities to learn their interests.

One of the potential problems with this research study design is the fact that the Cluztr plugin is currently in beta development. As of November 2008, the chief developer of Cluztr claimed that a major release of the plugin is in the imminent future. It is unknown at this point if all of the existing features of the plugin will remain in the next release.

Another potential problem is the Hawthorne Effect. If the research subjects are aware that the websites that they visit are being captured, their observed behavior may deviate from their normal behavior. When these research subjects are recruited, it must be made clear to them that the captured data are used to produce recommendations that may benefit their web browsing experience. The purposive sampling strategy will be able to reduce the Hawthorne Effect.

5.2 Option 2: Cross-Sectional Study

The second option is a cross-sectional research study of online music / radio listeners. Users of Pandora, a free online music discovery / recommending service, will be recruited to participate in this study. The profile of each subject is converted into an APML file using a web service provided by TasteBroker, which is a research project conducted by Sun Microsystems. The resulting APML file contains a series of recommended artists based on both explicit behaviors (e.g. searching, bookmarking) and implicit tastes (e.g. rating, skipping). Figure 2 below is an example of an APML file generated from TasteBroker. Each recommended artist has a corresponding *value* attribute between 0 and 1. The value represents a relative level of confidence in which the recommender believes the user will enjoy the music from the respective artist.


```
– <Profile name=”Music-Recommendations”>
  – <ImplicitData>
    – <Concepts>
        <Concept key=”The Guess Who” value=”1.0” from=”tastebroker.org” updated=”2008-11-24T23:58:11”/>
        <Concept key=”Cat Stevens” value=”0.97552097” from=”tastebroker.org” updated=”2008-11-24T23:58:11”/>
        <Concept key=”Graham Nash” value=”0.9485249” from=”tastebroker.org” updated=”2008-11-24T23:58:11”/>
        <Concept key=”America” value=”0.93791384” from=”tastebroker.org” updated=”2008-11-24T23:58:11”/>
        <Concept key=”Jim Croce” value=”0.93466264” from=”tastebroker.org” updated=”2008-11-24T23:58:11”/>
        <Concept key=”Crosby, Stills, Nash & Young” value=”0.9275277” from=”tastebroker.org” updated=”2008-11-24T23:58:11”/>
        <Concept key=”Tom Petty and the Heartbreakers” value=”0.90796405” from=”tastebroker.org” updated=”2008-11-24T23:58:11”/>
        <Concept key=”Don McLean” value=”0.90220994” from=”tastebroker.org” updated=”2008-11-24T23:58:11”/>
        <Concept key=”Donovan” value=”0.9008911” from=”tastebroker.org” updated=”2008-11-24T23:58:11”/>
        <Concept key=”Joan Baez” value=”0.8933352” from=”tastebroker.org” updated=”2008-11-24T23:58:11”/>
        <Concept key=”Albert Hammond” value=”0.88024837” from=”tastebroker.org” updated=”2008-11-24T23:58:11”/>
        <Concept key=”Van Morrison” value=”0.8775349” from=”tastebroker.org” updated=”2008-11-24T23:58:11”/>
        <Concept key=”Free” value=”0.8701583” from=”tastebroker.org” updated=”2008-11-24T23:58:11”/>
        <Concept key=”Paul Simon” value=”0.8694084” from=”tastebroker.org” updated=”2008-11-24T23:58:11”/>
        <Concept key=”Marianne Faithfull” value=”0.8559477” from=”tastebroker.org” updated=”2008-11-24T23:58:11”/>
        <Concept key=”James Taylor” value=”0.8509131” from=”tastebroker.org” updated=”2008-11-24T23:58:11”/>
        <Concept key=”The Outfield” value=”0.84817046” from=”tastebroker.org” updated=”2008-11-24T23:58:11”/>
        <Concept key=”Jackson Browne” value=”0.84539163” from=”tastebroker.org” updated=”2008-11-24T23:58:11”/>
        <Concept key=”Bob Seger” value=”0.8420915” from=”tastebroker.org” updated=”2008-11-24T23:58:11”/>
        <Concept key=”Carole King” value=”0.8387869” from=”tastebroker.org” updated=”2008-11-24T23:58:11”/>
        <Concept key=”Status Quo” value=”0.8381035” from=”tastebroker.org” updated=”2008-11-24T23:58:11”/>
        <Concept key=”Steve Miller Band” value=”0.83510864” from=”tastebroker.org” updated=”2008-11-24T23:58:11”/>
        <Concept key=”Bachman-Turner Overdrive” value=”0.8309556” from=”tastebroker.org” updated=”2008-11-24T23:58:11”/>
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Figure 2 Example of APML file generated by TasteBroker

Data will be collected in the form of a web-based questionnaire from each subject. After the subjects are chosen, they will be contacted through e-mail to access a personalized questionnaire. The questionnaire will be accompanied by a page explaining the purpose and relevance of the study as well as assuring them of anonymity. If subjects agree to participate in the study, they will be asked to specify the number of months and/or years they have utilized Pandora. Based on the APML files generated, subjects will be asked to rate on up to 10 artists from their lists of recommendations. The ratings are on a scale of 1 to 10, where 10 is the most favorable. Subjects are also allowed to give a rating of “N/A” if an artist is unfamiliar to them. These ratings will be compared against their corresponding values in each of the APML files.

This cross-sectional research study provides a quantitative measurement of the accuracy of attention profiling. Accuracy is measured by the relevance of the provided recommendations (i.e. how close do the recommendations match a subject’s actual music taste). However, this is only a relative measurement, meaning that the values provided in the APML file only indicates a relative level of confidence, and not an absolute assessment of likes and dislikes. For instance, if the values for two of the recommendations are 0.1 and 0.9 on a scale between 0 and 1, respectively, it does not mean that the subject will probably reject the first recommendation while accepting the second. It only means that the recommender is more confident about recommending the second artist than the first. Nevertheless, this quantitative study will allow us to measure the relevance of recommendations generated from attention profiling.

We will employ a non-random, quota sampling strategy to recruit 60 total users of Pandora to participate in this study. Subjects will be recruited from various means: blog on Pandora, researchers’ correspondence and their respective networks (i.e. snowball sampling). Based on the simplicity and non-invasiveness of the questionnaire, we anticipate the response rate of the questionnaire to be high. The 60 users are divided into 3 groups of 20 users. The characteristic of the 3 groups is based on the amount of time they have spent using Pandora. The first group is for users who have used this service for fewer than 1 month (beginners); the second group for users between 1 month to 1 year (immediate); and the third group for users longer than 1 year (long term). This strategy is utilized to determine whether time is a factor that affects the accuracy and relevance of the recommendations from attention profiling.

An advantage with this research study design is the fact that subjects will be more willing to share their opinions about their music tastes than web browsing interests in general. In Pandora or other online music stations, their users are constantly monitored both explicitly (e.g. search queries) and implicitly (e.g. ratings) to derive their music tastes. For users who utilize multiple online music stations, attention profiling can potentially build a more complete model of the users. In addition, the simplicity of the questionnaires can potentially increase the response rates from chosen subjects. Questions in regard to demographic information of the subjects will be kept to minimal.

A weakness of this study is the method of determining relevancy. For an experiment that evaluate relevancy of text documents, subjects are typically asked to judge based on some sort of representations of the documents (e.g. title, abstract, summary). In this study, users are asked to evaluate relevancy solely based on the names of the artists. Furthermore, the current implementation of TasteBroker lacks the ability to provide recommendations to a specific track of an artist. Besides the fact that the subjects may not be familiar with a particular artist, it may sometimes be difficult for the subjects to give a numeric ratings to artists alone. For instance, a subject may like a song from an artist while he/she dislikes another song from the same artist.

6. Work Schedule

After the completion of this class, we will continue to evaluate the strengths and weaknesses of both research study designs and select one of the designs to proceed.

The study will start in February or March of 2009 and will take approximately 6 months to complete. This timeframe includes data collection, analysis, and reporting. Table 1 below is a breakdown of the work schedule.

Activity	Option 1: Case Study	Option 2: Cross-Sectional Study
Recruit Participants	2 weeks	4 weeks
Collect Data	12 weeks	6 weeks
Analyze Data	4 weeks	8 weeks
Report	6 weeks	6 weeks
Total	**24 weeks (6 months)**	**24 weeks (6 months)**

Table 1 Work Schedule

7. Structure of Research Report

The structure of the research report will be organized into the following sections:

Section 1: Introduction

Section 2: Background

Section 3: Research Problem and Methodology

Section 4: Results

Section 5: Discussion

Section 6: Conclusions and Future Work

8. References

Davenport, T., & Beck, J. (2001). *The Attention Economy: Understanding the New Currency of Business* (Vol. 2). Boston, Massachusetts: Harvard Business School Press.

Goldhaber, M. (1997, November 27). The Attention Economy and the Net. *TP: The Attention Economy and the Net*. Retrieved October 16, 2008, from http://www.heise.de/bin/tp/issue/r4/dl-artikel2.cgi?artikelnr=6097&mode=html&zeilenlaenge=72.

Heyman, K. (2008). The Move to Make Social Data Portable. *Computer*, *41*(4), 13-15.

Najjar, J., Duval, E., & Wolpers, M. (2006). Towards Effective Usage-Based Learning Applications: Track and Learn from User Experience (s). In (pp. 1022-1024). Washington D.C.: IEEE Computer Society.

Najjar, J., Meire, M., & Duval, E. (2005). Attention Metadata Management: Tracking the use of Learning Objects through Attention.XML. In (pp. 1157-1161). Montreal, Canada.

Najjar, J., Wolpers, M., & Duval, E. (2006). Attention Metadata: Collection and Management. In . Edinburgh, UK.

Ochoa, X., & Duval, E. (2006). Use of Contextualized Attention Metadata for Ranking and Recommending Learning Objects. In (pp. 9-16). New York: ACM.

Quiroga, L., Crosby, M., & Iding, M. (2004). Reducing Cognitive Load. In *Proceedings of the 37th Hawaii International Conference on System Sciences*. Washington D.C.: IEEE Computer Society.

Quiroga, L. M., & Mostafa, J. (2002). An experiment in building profiles in information filtering: the role of context of user relevance feedback. *Information Processing and Management*, *38*(5), 671-694.

Roda, C., & Nabeth, T. (2007). Supporting Attention in Learning Environments: Attention Support Services, and Information Management. *Lecture Notes in Computer Science*, *4753*, 277-291.

Vertegaal, R. (2002). Designing Attentive Interfaces. In (pp. 23-30). New York: ACM.

Vuorikari, R. (2008). Consolidating Collections of Learning Resources using APML. In (Vol. 8).

Wolpers, M. (2008). Contextualized Attention Metadata in Learning Environments. *The European Journal for the Informatics Professional*, *IX*(3), 57-61.

Wolpers, M., Martin, G., Najjar, J., & Duval, E. (2006). Attention Metadata in Knowledge and Learning Management. In (Vol. 6).

Wolpers, M., Najjar, J., Verbert, K., & Duval, E. (2007). Tracking Actual Usage: the Attention Metadata Approach. *Educational Technology and Society*, *10*(3), 106-121.