Emotion-Based Recommender System for Overcoming the Problem of Information Overload

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Abstract. Nowadays, we are experiencing a huge growth in the available information, caused by the advent of communication technology, which humans cannot handle by themselves. Personal Assistant Agents can help humans to cope with the task of selecting the relevant information. In order to perform well, these agents should consider not only their preferences, but also their mental states (such as beliefs, intentions and emotions) when recommending information. In this paper, we describe an ongoing Recommender System application, that implements a Multiagent System, with the purpose of gathering heterogeneous information from different sources and selectively deliver it based on: user's preferences; the community's trends; and on the emotions that it elicits in the user.

Keywords: information overload, multiagent systems, personal assistant agents, recommender systems, user modeling.

1 Introduction

The recent explosive growth of information (e.g., in the World Wide Web) has made critical the need for intelligent assistance when users browse, search and explore for interesting information. With new data being created everyday (e.g., in social networks as Facebook, Twitter and online newspapers), humans continuously receive a superabundance of information, which they cannot handle by themselves [7,12]. Moreover, as the number of people and subjects being followed increases, the time required to get through to the social updates they emit also increases, causing a loss of productivity. Additionally, as social updates are broadcast in real-time, humans are frequently interrupted, with can reduce their ability to focus on a demanding task, especially when the social updates are not relevant for their current task (i.e., the interruption could induce a costly cognitive disruption).

In this context, Personal Assistant Agents (PAAs) can be used to retrieve, filter and recommend only relevant information to the user [12,13,14]. Actually, in the last years there has been a remarkable interest in the development of PAAs. These agents have been successfully integrated in available mobile devices and made their way to the general public. One of the most popular is SIRI[1], a PAA developed by the homonymous company bought by Apple in 2010, and whose technology is now fully integrated into the iPhone 4S. Google released "Google move" after buying CleverSense[2], a company that developed ALFRED/Seymour PAA. More recently, Nuance, the company behind the speech recognition technology in the Siri and dictation features on the iPhone, iPad and OS X, has released a new Siri-like API called Nina[3]. Nina virtual assistant persona, as the company calls it, enables natural conversation, by understanding what users say and mean, and also remembers the context of what is said to refine the results. Even chatbot technology has recently seen a renewed and rising interest with Existor[4] and the chatting software developed by Cleverbot[5] and Tayasui[6].

However, personalised, contextualised and emotional Recommender System (RS), that implements a Multiagent System (MAS) and also integrates heterogeneous sources, are still to come [12]. The user's interests involves a wide range of domains (e.g., politics, sport), which are physically or logically distributed (in terms of their availability and sources). Consequently, it is mandatory to have some kind of retrieval system capable not only of gathering information, but also of filtering it selectively, according to the interests and emotions that this information elicits in the user. For example, nowadays people do not want, or do not have the necessary time, to read all the feeds subscribed, catch up with all the events that will occur or all their friends social notifications [18]. As far as we know, especially concerning the Portuguese language, the literature approaches do not overcome the aforementioned problems. More precisely, they do not take into consideration people's intentions and desires, combined with their social networking habits and also the community trends, into real usable RS application. In order to accomplish that, a MAS will be embedded with the purpose of provide selective information to the users [12].

We believe that it is possible to create an emotion-based RS application, with individual users' agents, capable of filter out irrelevant or emotionless information [12]. Thus, the system needs to handle the people's mental states and also to understand that everyone is different from each other, i.e., everyone has different desires, intentions, interests and motivations to read a specific piece of information [25,21,13]. In order to overcome this information overload problem [7], we identified five tasks that our system needs to be able to perform: *collect* information from different sources; *extract* information from the news, e.g., facebook notifications, tweets or daily news [33]; *represent* the extracted information into a structured representation [35]; *share* information between

[1] `www.apple.com/iphone/features/siri.html`
[2] `www.thecleversense.com`
[3] `www.nuance.com/meet-nina`
[4] `www.existor.com`
[5] `www.cleverbot.com`
[6] `www.tayasui.com`

agents, e.g., users' preferences and emotional features [17]; *deliver* information based on the learned or expected human's preferences, intentions and goals, taking advantage of the structured knowledge and the agents community [21].

2 Related Work

Recommender Systems (RS) can be categorised into three main categories [4]: Collaborative Filtering (CF), Content-Based (CB), and Hybrid approach which combines the previous two methods. The first experiments in the RS area adopted pure CF approaches [8], which consist in calculating similarities among users. Knowing the user's neighbours (users with similar opinions or tastes), the system recommends items according to the neighbours' preferences. In fact, with this approach, as more users rate items, more accurate the recommendations become. There are two main paradigms in this approach: *model-based* and *memory-based* techniques, being the latter one the dominant paradigm. In contrast to memory-based CF, where it is used the entire user-item rating dataset to generate a prediction, the model-based CF technique groups different users from the training database into a small number of classes based on their rating patterns.

Another possible approach in RS is CB recommendations, which consists in giving recommendations to a user, based on his past data or personal preferences [26], without involving data from other users. To make that possible, RS must be able to extract content from the items, to verify which content correlates the most with the user's preferences [26]. For example, some works show promising results in different domains, e.g., movies and books [27,28]. Both works used Information Extraction (IE) and text categorisation to create descriptions of products, with the purpose of analysing their similarities with the users' profiles.

Both CB and CF approaches have advantages, but also some shortcomings. Pure CB systems, in some domains, can have problems in the IE process, i.e., some content can be hard to be structured and classified [6]. Another problem that can occur is *overspecialisation* [6]. If the system is programmed to only recommend items with high similarity to the user's previous preferences, the user will never receive recommendations of other types of items. On the other hand, pure CF systems suffer from *cold-start* problems [37]. Whenever a new item is added to the system's database, it does not have any rating, which makes it impossible to be recommended to any user. If a user has unique tastes, and no one has rated the 'same' items he did, he will not receive any recommendations. A similar problem can also occur if the number of items in the database is much larger than the number of users, which makes it difficult to find users that have rated the same items [6].

All these problems led various authors to experiment hybrid RS that merged CF and CB approaches [6,8,37]. These systems have been applied to various domains, such as adaptive hypermedia, content personalisation and user profiling [6,8]. Hybrid recommenders combine users' ratings (CF) with meta-data about the items (CB). Consequently, they overcame some of the problems that each of the previous approaches had.

More recently, several authors have been trying to use context in RS. However, having the user's context in consideration adds an additional dimension of complexity to RS, hence ratings may be valid in only one particular context [40]. Nevertheless, RS can be improved by enrichment with various sorts of contextual information (e.g., relationship among users in social media sites, collaborative tagging, background message of items, timestamp of user actions [10,3]. In the literature, context – for example in ubiquitous and mobile context-aware systems – was initially defined as the location of the user, in order to identity people and objects around him, and the changes in these elements [38]. Therefore, other factors have been added to this definition (e.g., date, season, and temperature) [9]. Some associate the context with the user [15], while others emphasise how context relates to the application [34]. An overview of the notions of context can be found in Adomavicius et al. [2].

Despite of several approaches proposed and new dimensions added to RS, most of the existing RS applications do not take information about human emotions [31] into consideration when recommending information [16]. Consequently, recommender applications are commonly unable to adapt to the constantly changing and evolving users' preferential states. This is partially caused by the difficulty of categorising and representing emotional states [30,39].

Nevertheless, an innovative system, addressed to the restaurant domain, is presented in [16]. In this work, a new approach to model users for RS based on the emotional factor, is described. The model they developed takes into account different attributes related to emotions, which purpose is capturing personality features of a user, e.g., familiarity (confidence) in customer's relationships; degree of patience that a user has on waiting for being served; the efficiency the user needs to feel; and the curiosity to know exotic restaurants. According to the authors, by adding emotional features to the user profile, recommendations are improved regarding the degree of acceptance from the user. It is important to refer that this model is developed taking into account both a CB approach on the information of an isolated user, and a CF approach based on the information provided by the users' community.

More recently, Mostafa et al. [5] presented the Emotion Sensitive News Agent (ESNA), whose purpose is to categorise news stories from different RSS sources into eight emotion categories, according to their emotional content. However, in this approach the affective information conveyed through text is analysed by using a *rule based* approach to assign a numerical valence (i.e., a positive or negative value to assign positive or negative sentiment to the input text). Additionally, the recommendation process considers the cognitive and appraisal structure of emotions [29], and also takes into account the users' preferences.

To sum up, there is a lack of research on applications that use emotion 'in context', and this ability to detect emotions explicitly or even implicitly will add a rich dimension to RS applications.

3 Approach

Figure 1 presents the proposed main components for the emotion-based RS. This system architecture can be seen as a *middleware* between the user's needs (explicit or implicit [22]) and the available information. Its purpose is to deliver information to the user in a selective fashion. As we know, user's intentions and actions are not usually isolated processes, but tend to be influenced by their social environment [18]. However, identifying a user's goals and intentions is not a straightforward task, relying on complex plan recognition [19]. Thus, besides considering the user's model (i.e., preferences, intentions and emotions, represented in the figure 1 as *individual knowledge* and *emotional features*), the agent (PAA) should also contemplate the social networking trends. In the context of this work, trends consist of new data that elicits novelty, surprise or even curiosity in the system community. For this matter, the implementation of collaborative agents to share and discover new trends is imperative.

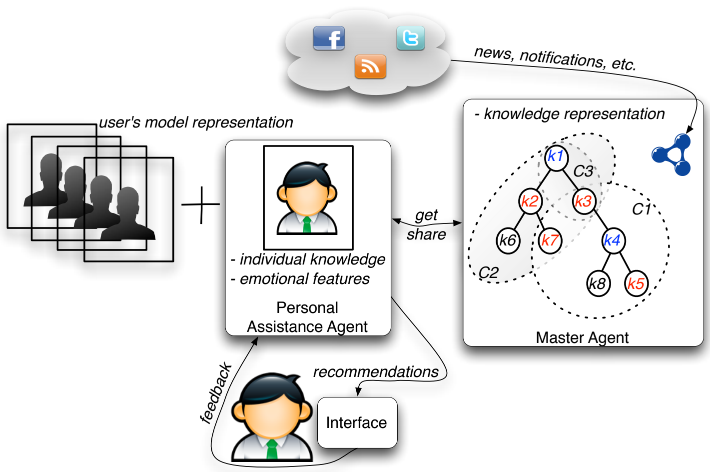

Fig. 1. Emotion-Based RS's Architecture.

The user's agent will work as a selective recommender filter. It will compare its user model with the others PAAs and infer new potentially interesting information, even if not suitable for the user's list of implicit preferences [41]. Briefly, these agents will operate in an environment where some of their individual knowledge is shared.

For the system to perform well, it will be necessary to create a structured knowledge representation that these agents can take advantage of when performing tasks. This structure needs to incorporate both the gathered information and the social trends given from the users' *feedback* [36] (e.g., number of views for a specific item and its emotional impact). The emotional impact could be measure by asking the user what was the emotion that a specific information causes in him.

Another system requirement is the use of keyphrases to group sets of similar items (represented in figure 1 as k_n and C_n, respectively). Keyphrases provide a brief summary of a document's contents. More specifically, keyphrases are a concise representation of documents. As large document collections, such as news articles, become widespread and are created every second, the value of such summary information increases. Thus, keyphrases are particularly useful because they can be interpreted individually and independently of each other. Moreover, keyphrases are usually chosen manually [1]. Despite less prone to errors, this task is hardly repeatable, time-consuming and sometimes subjective. Consequently, our system needs to extract keyphrases from heterogeneous Web sources and represent it into a formal representation, in a completely automatic fashion.

The approach we propose for extract information from heterogeneous sources also needs to take into account the news' polarity. A basic task in sentiment analysis is classifying the polarity of a given text at the document, sentence, or word level - whether the expressed opinion in a document, a sentence or word is positive, negative, or neutral (presented in figure 1 as k_n, in different color tones). Commonly, this is done by determining the keyphrases polarity using automated ML algorithms, such as latent semantic analysis or support vector machines. More sophisticated methods can detect the holder of a sentiment (i.e., the person who maintains that affective state) and the target (i.e., the entity about which the affect is felt) [20]. In the future, we intend to relate the user's model with the news' polarity, for example by taking advantage of the SentiLex[7], to recommend only news that satisfies the user's emotional preferences.

The resulting knowledge base will make easy the retrieval by browsing and searching. Furthermore, it will allow clustering information into broader categories. To identify these domains, presented in figure 1 as C_n, it will be necessary to create associations between "close in context" objects. Specifically, clustering algorithms will be used to classify similar objects into different groups – more general topics than simple keyphrases – that will be used to send a list of main topics to the user, in order to start modelling the user's preferences and solve the cold-start problem.

Another method in the knowledge representation process that we intend to take advantage of, is collaborative keyphrasing, when available in the sources. In order to understand the benefits and limitations of using social generated keyphrases for indexing and retrieval purposes, it is important to investigate: to what extent the community influences keyphrasing behaviour; their effects in the represented knowledge; and whether this influence helps or hinders search and retrieval in our knowledge base. Indeed, some Web sources already use social keyphrasing (e.g., Twitter and Delicious) to identify topics of interest. Another important system requirement is its aggregation feature, i.e., we need to develop an aggregator component capable of gathering items from a wide number of Web-sources, such as Facebook, Twitter and RSS feeds.

[7] http://dmir.inesc-id.pt/project/SentiLex-PT_02

4 Experimentation and Evaluation

The experimentation phase starts with the definition of the evaluation process that will be applied to the system described in the approach section. The experimentation should be taken using data from real world usage with field tests. The system must be evaluated taking into account the interaction of the user with the system. Firstly, explicitly feedback given by the user will be used to access the system accuracy. Then, the accuracy will be inferred by the system, using an implicit feedback mechanism (like total reading time and past click behaviour [11,24].

4.1 Information Extraction

The utility of the extraction methods and knowledge extracted must be evaluated taking into account the *quality* and the *quantity* of the data extracted. The quality depends on the amount of keyphrases that are correctly identified, and the quantity depends on the number of keyphrases extracted among those that should have been extracted. There exists two main evaluation approaches: manual evaluation and the use of gold standard.

Manual Evaluation is the most classic type of evaluation. Due to its complexity, it is sometimes easier to transmit the principles that should be considered in the evaluation process to human judges, rather than encode a system to automatically evaluate the resource according to these principles. Most of the times, automatic evaluation can not be used, being the evaluation done manually by relying heavily on time consuming work from domain specialists. The disadvantages are: monotonous work, hard to repeat and also subjective to the judge's criteria. Gold Standard is a resource (e.g., could be another knowledge base) that certainly is correct – possibly because it was manually created by specialists. The new resource can be compared to a golden standard according to some criteria in order to assess its accuracy. Usually there are used three common measures in Information Retrieval, precision, recall and F_1.

For the purpose of this work, if possible a golden standard will be used to analyse the results' reliability, Besides that, manual evaluation of a small but representative part of the results need to be performed, in order to analyse the various stages of the development.

4.2 Recommendations

As we already mentioned, the aim of a RS is to predict appreciable items to the user. To do that we strongly believe in our approach to provide selective recommendations according to the user's preferences. However, the expected results from this hypothesis are likely to be subjective, since it cannot be measured accurately because their interpretation may vary under the user's perspectives. Nevertheless, the system must be evaluated taking into account the quality of the data recommended through the PAAs according to several

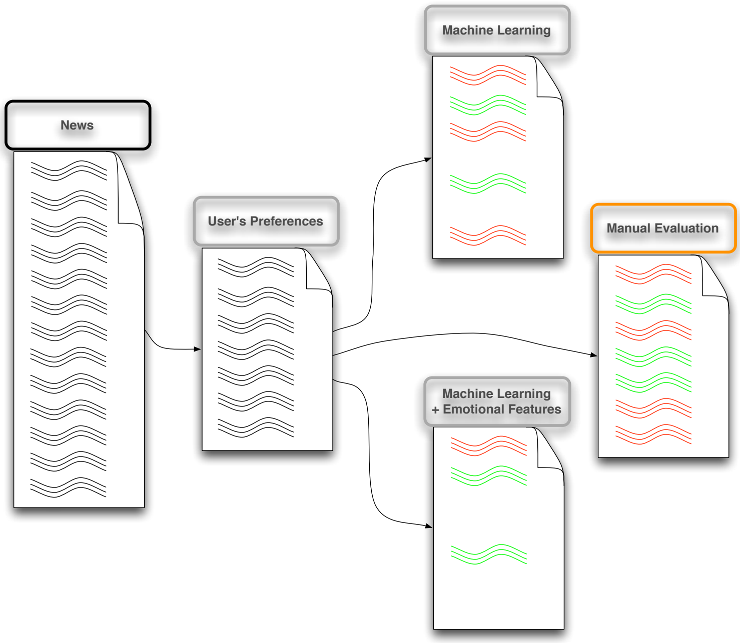

Fig. 2. An example scenario of the evaluation process.

defined evaluation' metrics, as well as in terms of the system's performance and usability.

The recommendations' quality will depend on the amount of items that are correctly recommended, which can be measured by analysing the users' feedback. To test the system' accuracy, we intend to observe the relationships between the manual evaluation and the output values given by both Machine Learning (ML) and ML with emotional features. In figure 2, we present an example scenario of the evaluation process. On the left, with label "*News*", we have all the news stored in the system, then, after choosing his preferences (with label "*User's Preferences*") the user will receive only news from specific thematics. However, this is not enough to prevent the users from receiving irrelevant information, as we show on the right side of the figure, with label "*Manual Evaluation*", where the green and red items represent interesting and not interesting items to the user, respectively. But, accordingly to the scenario in the figure, our assumption is that using ML and ML with emotional features it will be possible to improve the system' accuracy (labels "*Machine Learning*" and "*Machine Learning + Emotional Features*", respectively). After analysing the results from the situation presented in figure 2, it is expected higher accuracy when using ML with emotional features techniques, than without using them (see table 1). In short, our assumption can be considered very promising, being a good starting point.

The performance is commonly evaluated through the time the system consumes while executing the expected tasks, but also relates to how the system scales and keeps responding under different circumstances.

To evaluate the usability, questionnaires will be used to assess users' satisfaction. Still concerning usability, before starting the interface implementation process, we intend to make questionnaires to humans in order to identify their needs. For instance, to understand how they would like to consult the news, what is the better way to provide feedback and to recommend news to others.

Table 1. Results from the scenario presented in figure 2.

	Precision(%)	**Recall**(%)	$\boldsymbol{F_1}$(%)
User's Preferences	≈43	100	≈60
Machine Learning	60	≈66	≈63
Machine Learning + **Emotional Features**	≈66	≈66	≈66

5 Expected Contributions

In this work, our goal is to develop a RS that delivers information in a selective fashion. Given the user's expectations and the sources at our disposal, it will be imperative to create a system that performs near real time. To do that, and taking advantage of the belief-desire theory of emotion [32], as well as of the techniques developed in the fields of Artificial Intelligence, RS, Natural Language Processing, MAS and Affective Computing, we will create an emotion-based RS (described in the previews section). The expected outcomes are:

- ◇ Knowledge extraction from assorted sources and contexts into a structured representation.
- ◇ Beyond the standard data available on the Web (e.g., daily news), we intend to study how can RS benefit from social networking integration (such as friends recommendations, i.e., facebook notifications and tweets). Moreover, we intend to answer the question: – Will social networking integration increase the users usage and contributions in our application?
- ◇ A comparative view of the most common algorithms used to identify keyphrases. Study the most suitable metrics to weight keyphrases and how these metrics may be used to identify clusters (crucial to learn main categories in the knowledge base).
- ◇ Not only analyse for how long past information may be considered useful for the system, but also for the users [23].
- ◇ Identify the best structure to represent all the knowledge produced, not only the extracted data but also the information created by the agents (e.g., feedback and emotional features).

◇ Create dynamic and automatic user's models and study which are the most suitable for the users' demands.
◇ Analyse the impact of sharing information among the agents in order to answer this question: – Does the introduction of collaborative recommendations improve the system's trust?
◇ Finally, and most important, analyse if the affect-based PAA avoid their human owners from receiving irrelevant or emotionless information, outperforming the non-affect-based ones. Analysing the impact of affective features in the recommendations' accuracy.

Information overload has many negative implications, not only in personal life, but also in organisations, business and in the world economy in general [7]. As a result, this work intends to minimise some of these negative implications in human life. Although this work is directed for Portuguese, we intend to perform some experiments in English, in order to contribute and receive feedback from the international community. Furthermore, it is our intention to apply the resulting contributions in other application domains, such as navigation systems.

6 Concluding Remarks

The research proposal presented in this article is an answer to the growing demand on RS. More precisely, it addresses the lack of emotion-based RS, specially concerning real-time textual information. The importance of this kind of systems has been shown and, as far as we know, there is no research in this area for Portuguese or even for English.

This work will be focused in the development of a RS capable of filtering irrelevant and emotionless news to the user, by using a MAS approach and taking advantage of techniques developed in the fields of Artificial Intelligence, RS, Natural Language Processing, MAS and Affective Computing. Firstly, it will be implemented an aggregation module to acquire daily news from heterogeneous sources. Then, information extraction techniques will be used to extract the most relevant items. These items will be stored in a knowledge base that will provide support to the user's agent, when retrieving and storing information. These PAA will take advantage of their model and the community trends when recommending a new piece of information.

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