Using Images in Context-Aware Recommender Systems

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Abstract. In this paper, we propose a unified probabilistic framework for product recommendation which uses both images and user's contextual situation to predict accurately the ratings. In addition, this framework suggests highly rated and diversified products to reach better user satisfactions in conformance with researches in consumer psychology. Experimental results show that images improve the usefulness of recommendation comparatively with state-of-art methods.

Keywords: Recommender systems, context-awareness, content-based image suggestion, information filtering, ranking by diversity, clustering

1 Introduction

The widespread of Internet has promoted many e-commerce services over the world wide Web. For instance, on eBay.com or Amazon.com, it is possible to sell almost everything such as books, DVDs, clothes, etc. Generally, consumers purchase products to satisfy their long-term needs which are relatively stable, regular and refer to periodic preferences. For example, a user interested by fashion, would like to receive periodically items (product highlights, news) related to new fashion clothes, shoes or accessories. Recommender systems are software tools which predict the buyers long-term needs in order to suggest relevant products satisfying these needs. They help users to save a valuable search time spent before purchasing products by reducing the number of choice alternatives. For instance, Amazon.com suggests products to its users based on their historical data of ratings. A rating is a numerical value defined on an ordered scale and quantifies the users interest in the rated item (explicit preference indicator). From online retailers' point of view, recommender systems constitute an efficient advertisement strategy which personalizes highlighted products in order to acquire new potential consumers and retain existing ones.

Recommender systems predict the buyers' needs based on the collected historical data. The historical data can be seen as a user-product matrix where each entry (u, p) is the rating provided by user u to the product p. Due the availability of a huge amount of products, the proportion of empty entries in the user-product matrix is extremely high. Then, recommender systems first start by predicting the missing ratings (empty entries) corresponding to unseen products using information filtering techniques [2]. After that relevant items are identified as those having the highest predicted rating. It has been noticed in literature that the accuracy of the rating prediction is increased by exploiting the both information about the user's context and products.

Context-awareness in recommenders has been motivated from researches in consumer psychology which recognize the dependence of user long-term needs on the time, location, and any information about the physical environment surrounding the user [3]. It introduces an additional level of personalization by considering the influence of the external environment of the user on his/her appreciation of the products [21, 6]. For instance, location-based recommender systems exploit the contextual information defined by the user's geographical location (captured from user's mobile device) to suggest personalized advertisements of products in neighboring commerces.

Images constitute an other important factor influencing the usefulness of the recommendations. Note that many products such as jewelery or clothes are adopted by users because of their visual appearance which defines their look-and-feel in terms of the color, shape, and texture [10]. In some cases, the semantic information extracted from images may lead to better discrimination among image categories [13]. In the domain of marketing, images have been used as efficient means in advertisements since they can convey meanings that cannot be expressed using words [16]. For instance, images have been used successfully to present "highlighted products" in the Web site of many online retailers such as Amazon.com or eBay.com. This presentation style is motivated mainly by high persuasion power of images. In fact, a qualitative study published in 2005, shows how users are influenced by the product's visual appearance which carries information about aesthetics (emotional pleasure), functionality (number of offered options), or quality [8]. So far, the persuasive power of images on consumers has not been taken into account by rating prediction algorithms but only to present products. Thus, existing recommender systems do not model explicitly user long-term needs that related to the visual appearance of products expressed as "like product X of look-and-feel Y".

Once we have collected the data about users, products, contexts, and ratings, we need to design algorithms which model these data in a feature space to predict the missing ratings of unseen products. The majority of existing recommendation algorithms rank products by the predicted rating only. However, consumer psychology researches have shown that the variety-seeking behavior of the consumer pushes him/her to reduce the redundancy of some product attributes in consecutive purchase occasions. In fact, by diversifying choices, users reduce the risk of uncertainty caused by lack of expertise on some products, complement other already purchased products, or simply to avoid boredom [15]. In other words, the predicted rating is not a sufficient criterion to better satisfy consumers. Let us consider the example illustrated in Fig.1 which shows the suggestion lists of three products obtained using two ranking strategies where "laptop" is the product category having the highest predicted rating. If the rat-

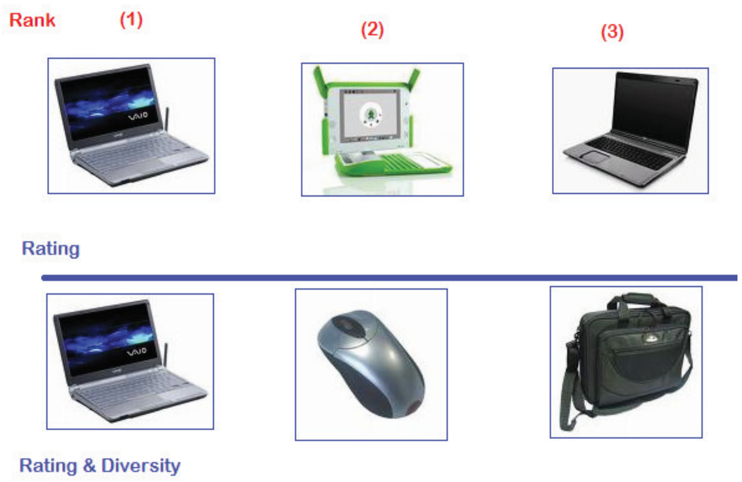


Fig. 1. Example of two suggestion strategies for given user interested by a "laptop".

ing is the only criterion for ranking products, it is natural that the first three suggestions are laptops since similar items receive similar ratings. Note that the second suggestion obtained by "rating & diversity" is more useful for both the user and online retailers since it provides diversified and complementary suggestions. Therefore, to reach highest user satisfaction, it is important to consider also the consumption history of each user to rank products by both predicted rating and diversity.

In this paper, we present content-based image suggestion (CBIS) which investigates the added-value of images and user contextual situations in making useful and diversified recommendations. We present our unified probabilistic approach which models seamlessly the uncertainty of the long-term needs of consumers, image collection, and the diversity of suggestions. This paper is organized as follows. In the next Section, we present recent advances in recommender systems. Then, we detail two ways of using images in improving the usefulness of recommendation algorithms. Experimental results are presented in Section 4. Finally, we conclude the paper with a summary of the work.

2 Related research work

During the last two decades, many relevant issues have been addressed in literature to increase the usefulness of recommender systems. In the following two subsections, we categorize recent advances in recommender systems at the levels of predicting accurately the ratings and ranking products by diversity.

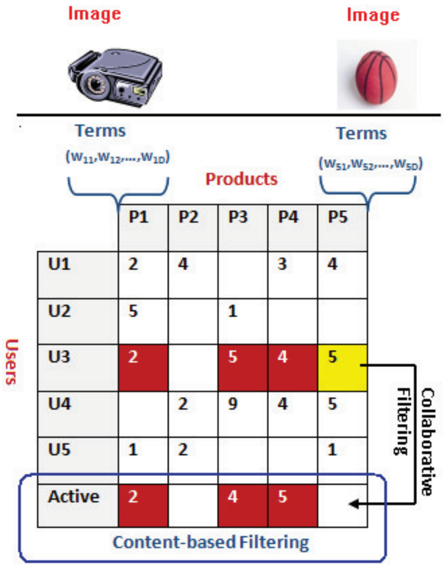


Fig. 2. Three major techniques of rating prediction. CBIS exploits the power of product images during the prediction of ratings.

2.1 Rating prediction

Recommender systems employ Information filtering (IF) technologies to predict the missing ratings for unseen products (e.g. empty entries in the user product matrix) [2]. In IF literature, there exist three families namely content-based filtering (CBF), collaborative filtering and hybrid methods. CBF employs information retrieval (IR) techniques in representing user profiles using content descriptors that are mainly defined by the textual information extracted from product captions, surrounding text in Web pages, etc (see "Terms" in Fig. 2). The principle of CBF methods is that items similar to those preferred by the user in the past, will be preferred in the future. For a given user, CBF classifies the ith product represented by word features $(w_{i1}, \dots, w_{iD})$ in the category of relevant or irrelevant products [17]. However, the major shortcoming of CBF is its inability to recommend to the user "unexpected" items different from what he/she has already rated in the past.

Collaborative filtering (CF) methods identify the neighbors of the user (other users with similar needs) based on ratings they provided on the same products. The neighbors are identified by analyzing the correlation among the rows of the user-product matrix. For example, in Fig. 2, $U3$ is the neighbor the active user since both of them liked the products P_3 and P_4 and disliked P_1. In CF, we find either distance-like methods [18] or model-based clustering-like techniques such as [12, 11, 19]. CF methods consider items as a categorical variable (i.e. unique index for each item) and are unable to suggest unseen items (novel products). Hybrid methods take advantages of both CF and CBF and identify both the neighbors of the user and products categories in making rating predictions [20]. For context-awareness, the authors in [1] define the contextual information as location, time, and compagnon. Then, many reduced user-product matrices specific to each context, are derived from the historical data. Then, a collaborative filtering technique is employed on the reduced matrix to predict the empty entries for a given context.

2.2 Ranking items by diversity

A natural way to promote the diversity is to eliminate the redundancy by considering the dissimilarity of each image with respect to previous consumptions according to some distance metric. Some normalization of term weights of the query can be resolved before accurately computing the distance metric [9]. Information retrieval has addressed the issue of ranking documents by diversity by a general two stage procedure as follows [22, 7]. The first document is selected as the one being the most similar to the query (topic). Then, documents are inserted successively into the result set according to both their similarity to the query and the redundancy they provide with respect to the already retrieved documents. The authors in [22] penalize the results with lower number of covered subtopics. The authors in [7], employ a probabilistic model for retrieval where the prior distribution (over word features) is updated successively each time a document is selected within the result set. Diversity-ranking methods have shown to reach better user satisfactions in retrieval tasks.

3 Content-based image suggestion

In this section, we investigate the use of product images instead of textual features, as shown in Fig. 2 in modeling the entries of the user-product matrix. Therefore, we consider images as a contextual information at the level of products defining their look-and-feel. For users, we investigate the added-value of the context defined by the external environment (location and time) in refining product recommendations.

3.1 Notations

We consider the following representation of the user-product matrix extended with both visual and contextual information. We have a set of users $\mathcal{U} = \{1, 2, \ldots, N_u\}$, a set of images $\mathcal{V} = \{\boldsymbol{v}_1, \boldsymbol{v}_2, \ldots, \boldsymbol{v}_{N_v}\}$, and a set of possible contexts $\mathcal{E} = \{1, 2, \ldots, N_e\}$. Each $\boldsymbol{v}_k$ is a visual descriptor used to represent the content (color, shape, texture) of products. For instance, it may carry information about the shape, color, or the texture present in images. We define the context as a combination of two attributes: location $\mathcal{L} = \{in - campus, out - campus\}$ inferred from the Internet Protocol (IP) address of the subject, and time as $\mathcal{T} = (weekday, weekend)$ i.e $N_e = 4$. The rating is expressed explicitly on an ordered scale defined as $\mathcal{R} = \{1, 2, \ldots, N_r\}$. For example, the five star scale (i.e. $N_r = 5$) such as the one used by Amazon.com, allows the users to give more detailed degrees of appreciation. The CBIS data set is defined as $\mathcal{D} = \{d^{(i)} =< u^{(i)}, e^{(i)}, \boldsymbol{v}^{(i)}, r^{(i)} > | e^{(i)} \in \mathcal{E}, \boldsymbol{v}^{(i)} \in \mathcal{V}, r^{(i)} \in \mathcal{R}, i = 1, \ldots, N\}$. Note that each observation $d^{(i)}$ is nothing else than an entry in the extended user-product matrix.

3.2 Using images to predict ratings

We consider the problem of CBIS as the maximization of a utility that ranks images for a user in a certain context. In this subsection, we exploit the power of images to define a more accurate utility which incorporates the information about both the rating and diversity.

Let $\mathcal{X} = \{x_1, x_2, \ldots, x_L\}$ be a list of L ranked images to recommend to a given user u in a context e where $x_t \in \mathcal{V}, t = 1, \ldots, L$, is the image at rank t in $\mathcal{X}$. The diversity of $\mathcal{X}$ imposes another condition that involves measuring dependencies (information redundancies) within subsets of products during the suggestion process. Therefore, the utility of the tth suggested product depends on both its rating and other products $\mathcal{X}_t = \{x_1, \ldots, x_{t-1}\}$ in the suggestion list that have been already consumed. The following utility function measures such compromise

$$x_t = \arg \max_{x \in \mathcal{V} - \mathcal{X}_t} s(x, u, e | \mathcal{X}_t) \tag{1}$$

To predict the ratings, we propose a generative model $p(u, e, x, r)$ which captures the joint probability (uncertainty) to observe a rating r for any entry (u, e, x). Note that one could predict probabilistically the rating using $p(r|u, e, x)$ obtained by conditioning $p(u, e, x, r)$ on (u, e, x, r). Based on product images, we consider similar users as those who have preferred similar images. For that end, we should first identify K user classes and M image classes from the observed data set $\mathcal{D}$. Then, two latent variables z and c label each data (u, e, x, r) with information about the user class and image class, respectively. We adopt the visual content flexible mixture model (VCC-FMM) [5]

$$p(u, e, x, r) = \sum_{c=1}^{M} \sum_{z=1}^{K} p(z)p(u|z)p(e|z)p(c)p(x|c)p(r|z, c) \tag{2}$$

The quantities $p(z)$ and $p(c)$ denote the *a priori* weights of user and image classes. $p(u|z)$ and $p(e|z)$ denote the likelihood of a user and context to belong respectively to the user's class z. $p(r|z, c)$ is the probability to generate a rating for a given user and image classes. Finally, $p(\boldsymbol{v}|c)$ is multi-dimensional continuous-valued generalized Dirichlet distribution (GD), parameterized by $2 \times d$-dimensional vector $\boldsymbol{\delta}_c$. We denote by Θ, the set of VCC-FMM parameters

$$\Theta = \big(p(z), p(c), p(u|z), p(e|z), \boldsymbol{\delta}_c, p(r|z, c)\big) \tag{3}$$

We train this model from the data $\mathcal{D}$ to identity the optimal parameters Θ_{ML} which maximize the log-likelihood of the data set $\log p(\mathcal{D})$

$$\Theta_{ML} = \arg\max_{\Theta} p(\mathcal{D}) = \prod_i p(u^{(i)}, e^{(i)}, x^{(i)}, r^{(i)}) \tag{4}$$

The numbers of user classes K and image classes M are unknown and their automatic identification from $\mathcal{D}$ is still a challenging problem in unsupervised learning. However, one could estimate automatically these numbers (M and K) from the data using minimum message length (MML) approach [5].

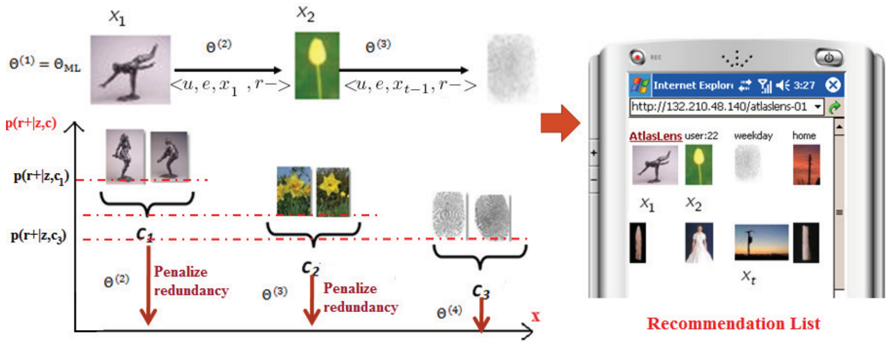


Fig. 3. The principle of our diversity-based ranking for suggesting highly rated and diversified images. Horizontal axis outlines the similarity of images while vertical axis defines the probability for an image to get a high rating. Images of the class c_1 (similar to x_1) are penalized by setting $p(r^+|z, c_1) \simeq 0$.

3.3 Using images in to rank by diversity

The diversity of the suggestion lists $\mathcal{X}$ can be measured as the degree of dissimilarity between all images in the list. Based on the visual information of products, we maximize both the diversity and the rating by an appropriate design of the ranking function $s(x, u, e|\mathcal{X}_t^{ue})$. Since consumers make binary purchase decisions (buy or not), we employ a binary scale $\{r^+, r^-\}$ for ratings. The products are ranked probabilistically according to a utility which favors those with high ratings as follows

$$s(x, u, e) = \log \frac{p(r^+|x, u, e)}{p(r^-|x, u, e)} \tag{5}$$

where $p(r^-|x, u, e) = \sum_{r=1}^{T_r} p(r|x, u, e)$, $p(r^+|x, u, e) = 1 - p(r^-|x, u, e)$ and T_r is a threshold used to separate positive and negative ratings.

Now, the principle of our diversity-ranking strategy is to recommend only "highly rated" products which belong to "different classes". Given that we have already recommended $\mathcal{X}_t$ products, we select the current one such that it is "visually" dissimilar from those in $\mathcal{X}_t$ by assuming previous products *"irrelevant"*. This assumption is implemented by generating negative ratings for the consumed products $\{< u, e, x_{t'}, r^- >, t' = 1, \ldots, t\}$. In order to take into account the new information about the irrelevance of $\mathcal{X}_t$, the parameters of the model $\Theta^{(t)}$ are successively updated from each observation $< u, e, x_{t'}, r- >$. Let $s(x, u, e; \Theta)$ be the utility (5) computed using a certain model Θ given by equation (3). Then, to promote the diversity, x_t^{ue} is selected according to the utility (1) and having the form (5) with $s(x, u, e; \Theta^{(t)})$ except that the parameters are updated with diversity information:

$$s(x, u, e|\mathcal{X}_t^{ue}) = s(x, u, e; \Theta^{(t)}) \tag{6}$$

The general scheme of our algorithm is given as follows. Initially, we set $\mathcal{X}_1^{ue} = \emptyset$ and $\Theta^{(1)} = \Theta_{ML}$ given by Eq. (4). Then, each time an image x_{t-1} of class c^*_{t-1} is suggested, we use a cost-effective online learning since an offline relearning is not a reasonable solution. The probability of positive ratings for images of the same class $p(r^+|z, c^*_{t-1})$ are updated effectively as [4]

$$\begin{aligned} &p(r^+|z, c^*_{t-1}) = 0, \\ &c^*_{t-1} = \arg\max_c p(c|u, e, x_{t-1}, r^+) = \frac{p(c, u, e, x_{t-1}, r^+)}{p(u, e, x_{t-1}, r^+)} \end{aligned} \tag{7}$$

with $p(c, u, e, x, r) = \sum_z p(z)p(u|z)p(e|z)p(c)p(x|c)p(r|z, c)$. Intuitively, Eq. (7) allows the selection of image class representatives with the highest predicted ratings. Therefore, the proposed diversity-ranking strategy seeks for "novel" products with high-ratings as illustrated in Fig. 3. The first product to suggest comes from the class "piece of art" in left since it has the highest rating. Once it is selected its probability of high-rating is reduced to zero. The second product to suggest will necessarily come from the class with the second highest rating (flowers). This process is repeated until the suggestion list is filled. Note that a rating-based ranking strategy can be implemented straightforwardly by considering constant parameters, i.e. $\Theta^{(t)} = \Theta_{ML}, \forall t$

$$s(x, u, e|\mathcal{X}_t^{ue}) = s(x, u, e; \Theta_{ML}) \tag{8}$$

4 Experiments

The aim of this experiment is to measure the contribution of the visual information in making accurate recommendations comparatively with state-of-art methods. We make comparisons with some representative algorithms used for rating prediction that are the Aspect model [11], Pearson Correlation (PCC)[18], Flexible Mixture Model (FMM) [19], the Decoupled Model (Decoupled) [12] and the User Rating Profile (URP)[14]. For CF approaches, we consider images as a categorical variable. To investigate the usefulness of contextual information, we evaluate the V-FMM which is the variant of VCC-FMM with only one (homogeneous) context information, i.e. $\mathcal{E} = \{1\}$. We measure the performance of algorithms in terms of both accuracy of predicting ratings.

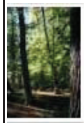
Classes	**c = 2**	**c = 11**	**c = 14**	**c = 28**
Images				
z = 1	0.21	0.08	0.74	0.17
z = 2	0.01	0.84	0.07	0.32
z = 3	0.88	0.32	0.92	0.06

Table 1. Sample visual content class representatives and the estimated probability of high rating $p(r^+|z, c)$, for a selected set of user classes.

Table 2. Averaged MAE with standard deviations over 10 runs of the different algorithms on $\mathcal{D}$. The relative improvement rates are computed by comparing MAe of each algorithm with that of PCC.

	PCC(baseline)	Aspect	FMM	URP	Decoupled	V-FMM	VCC-FMM
Avg MAE	1.327	1.201	1.145	1.116	1.095	0.890	0.646
Std Deviation	0.040	0.051	0.036	0.042	0.037	0.034	0.014
Improvement	0.00%	9.49%	13.71%	15.90%	17.48%	32.94%	55.84%

4.1 Data Set

We present experimental results conducted on a collected from 27 subjects who participated in the experiment (i.e. $N_u = 27$) during a period of three months. The participating subjects are graduate students in faculty of science (computer science, mathematics, biology, and chemistry). Subjects received periodically (twice a day) a list of three images on which they assign relevance degrees expressed on a five star rating scale (i.e. $N_r = 5$). A data set $\mathcal{D}$ of 13446 ratings is collected ($N = 13446$). We have used a general-purpose collection of 4775 images collected in part from Washington University and another part from collections of free photographs. The image collection which we experiment here contains both man-made and natural images and categorized into 41 categories. To represent images, we have employed both local and global descriptors. For local descriptors, we use the 128-dimensional Scale Invariant Feature Transform (SIFT) to represent image patches. We employ vector quantization to SIFT descriptors and we build a histogram for each image ("bag of visual words"). The size of the visual vocabulary is 100. For global descriptors, we used the color correlogram for image texture representation, and the edge orientation histogram. An image descriptor is a 140-dimensional

4.2 Prediction accuracy

Experiment protocol We divide the data set $\mathcal{D}$ into two halves: one for training VCC-FMM and the remaining part for validation. We measure the accuracy of the prediction using the Mean Absolute Error (MAE) which is the average of the absolute deviation between the ratings $r_{\boldsymbol{v}}^{ue}$ in the validation data $\mathcal{D}_{test}$ and the predicted ones $\hat{r}_{\boldsymbol{v}}^{ue} = \sum_r r(p(u,e,\boldsymbol{v},r)/\sum_r p(u,e,\boldsymbol{v},r)$

$$MAE = \frac{1}{|\mathcal{D}_{test}|} \sum_{d_i \in \mathcal{D}_{test}} |r_{\boldsymbol{v}^{(i)}}^{u^{(i)}e^{(i)}} - \hat{r}_{\boldsymbol{v}^{(i)}}^{u^{(i)}e^{(i)}}| \tag{9}$$

Results The first five columns of table 2 show clearly the added value of the visual content comparatively with pure CF techniques. For instance, the improvement in the rating's prediction reported by V-FMM is 22.27% and 19.81% comparatively with the recent CF approaches FMM and URP, respectively. VCC-FMM which takes into account the context information has also improved the accuracy of the prediction comparatively with the others (at least an additional 15.28%). From consumer psychology [3], this fact outlines clearly the influence of the contextual situation on user long-term needs.

4.3 Usefulness of suggestion lists

Experiment protocol This evaluation measures the effectiveness of rating-based and diversity-based ranking strategies in terms of user satisfactions. In each experiment run, we initialize $\mathcal{X} = \emptyset$ and we put $T_r = 3$ to separate negative (r^-) and positive (r^+) ratings. We collect satisfaction indicators from the human subjects who participated in the generation of that data set. Each subject is recommended eight images on each of which he/she attributes a binary relevance degree: "0" for not-relevant and "1" for relevant. Then, we evaluate quantitatively the usefulness of the suggestion using the precision computed as the proportion of relevant images in the the list.

Results Figure 4 shows that for rating-based ranking, the higher the size of suggestion lists, the lower the value of average precision. Also, the diversity-based ranking reaches better user's satisfaction (18.06% in average) than rating-based one. Indeed, by removing "visual redundancy", we improve the usefulness of suggestion lists which conforms with consumer psychology researches [15]. Finally, it is shown that the "optimal" size of suggestion lists, i.e. highest average precision, are four and eight images for rating-based and diversity-based suggestions, respectively.

5 Conclusions

In this paper, we have studied the contribution of the visual and contextual information in the improvement of the usefulness of recommender systems. The proposed model predicts the outcome of the user's decision making in each context based the preferences of other users with similar interests on product images. Experiments showed that images helped significantly in increasing the accuracy of rating prediction and usefulness of suggestion lists.

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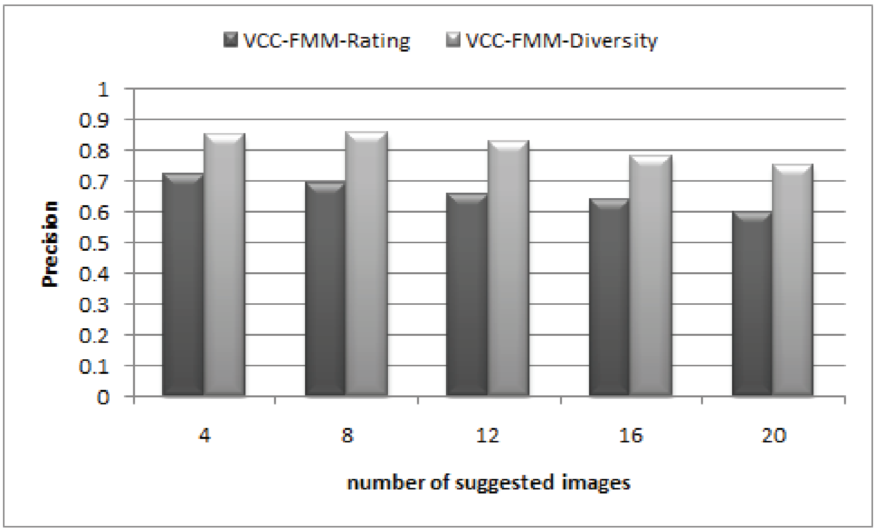

Fig. 4. Average precision reported by two ranking methods for building suggestion lists.

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A Profile Ontology for Personalised Mobile Shopping Support

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Abstract. Personalisation is a desired functionality for applications within mobile environments. One approach to personalisation of mobile services is by the use of personal and contextual information. In this paper we describe a personal profile for this purpose that has been created using OWL DL implemented in Protégé. The developed profile ontology is based on, and evaluated relative to, personas and scenarios from the food shopping domain. The profile covers three levels of information; personal information, stable information and temporary interest. The main result is a profile ontology that is used to illustrate potential benefits by use of information about a person in the personalisation process, which can be extended to cover other areas of interests.

Keywords: Personal profile, ontologies, personalisation, food shopping.

1 Introduction

New types of networks and devices bring the Internet into everyday lives through wireless and mobile technologies. Users of mobile technologies are getting exposed to information and services, without being able to control the flow of services. The goal is to connect accessible and mobile devices collecting context and eventually provide service provisioning for the users through the sharing of information in a ubiquitous computing environment [1]. This change will involve technical, social and organisational challenges [2].

The vision for the next generation Web as the Semantic Web [3], is now often combined with Web 2.0 technology to predict Web 3.0. Information is accompanied by metadata about its interpretation, so that more intelligent and more accessible information-based services can be provided. With these new possibilities we need to increase users' abilities to express what information and services they need. For our personalisation we will use Semantic Web technology as the enabler. The core components in the Semantic Web and its applications will be the ontologies. An ontology can be seen as an explicit representation of a shared conceptualisation [4] that is formal [5].

Personalisation is needed to overcome information overflow and the traditional one size fits all approach. By knowing the user one can improve the quality of services delivered. Information about a user can be used to target services directly to a specific user. One of the main challenges and potential for future contextualised and personalised support lies in the combination of public and private information and the combination of personalisation and contextualisation [6]. Research has been done on adapting information according to the context the user is in. However, little research has been done in focusing on offering the right services at the right time.

Here we focus on the personal profile. The developed case environment is related to food shopping, where users in some situations have to make non-trivial decisions. Mobile services within the food shopping domain is currently being investigated by the GS1 MobileCom [7]. We want the system to be able to decide what can be relevant in a particular situation. Depending on what the goal is for a specific user, varying parts of profile and context will assist in the personalisation process. Being on the move it is important for users to receive the right information at the right time, and at the same time being able to exchange and control information that is necessary to make this possible.

The rest of the paper is organised as follows. First, selected parts of our food shopping case are described. Then, the developed ontologies are described together with the necessary types of information about a person. Third, the overall architecture is presented. Related work is presented in section 5. Finally, conclusions are drawn.

2 Case Environment

The main sources of information for the creation of the profile are the personas and the scenarios. A persona describes users quite detailed, while the scenarios put the persona in a realistic situation.

2.1 Persona: Bill and his Family

A persona is a description about an imaginary user that explains who he is, his beliefs and goals etc. Such a description can therefore explain the decisions and choices he makes. Personas can be used as an interaction design technique with significant influence on development of new software [8]. They work as a shared basis for communication, and for engagement in the group that are going to use them [8, 9]. By understanding a fictitious user one is better prepared to be able to predict how a different person than himself would behave in a specific situation.

Our family personas consist of five persons; a mother, a father and three children, and they constitute a household. Family members have preferences and wants, and sometimes the preferences do not match. When there is a conflict, the parents have the last word. Here we focus on the father, Bill. These keywords describe Bill; 39 years old, conscious about contents of food, prefers healthy, non-harmful food, prefers ecologically produced food, small carbon footprint if possible, FairTrade is regarded positive, price is an issue, but not the most important one, have certain affinities, likes to have a preset shopping list and finds it difficult to adapt on the spot.

The shopping list of the day can be regarded as a temporary interest, while the preferences for certain makes and brands can be regarded as stable interest. Note that the temporary interest relative to today’s shopping list is recurrent at different intervals (e.g. if milk is bought today, it will typically turn up again the week after. Products that one does not get, might be replaced, or might stay on the list).

We understand that Bill and his family are interested in what they eat. When one is conscious about food, what it contains and how it is produced, it is important to easily find relevant information about products. However, it can often be challenging and time consuming to find this information manually on the declaration. Therefore assistance in the food shopping process is highly relevant for Bill.

2.2 Scenario: Bill Shopping Food

In this selected scenario, Bill is out shopping on a Tuesday evening. The shopping list was prepared in advance, and consists of items for the whole family. Bill finds it difficult to adapt on the spot, and consequently he prefers a complete shopping list in advance. The scenes are illustrated in Figure 1. Bill has strawberry jam on the list, but the type they usually buy is sold out. On the shelf there are many alternatives, and Bill does not know which one to choose. A jam has typically more than ten different types of information related to it. Since Bill has specific concerns regarding the contents of food, it is important for him to avoid certain ingredients. Instead of reading the declaration of contents for all the available strawberry jams, he provides a query for alternatives, a request, to the personalisation system (e.g. scanning the bar code of an available jam and select alternative product). The result of the request is a response from the system, which is a prioritised list of jams according to his preferences and the knowledge about the different jams (and of the jam that is originally preferred).

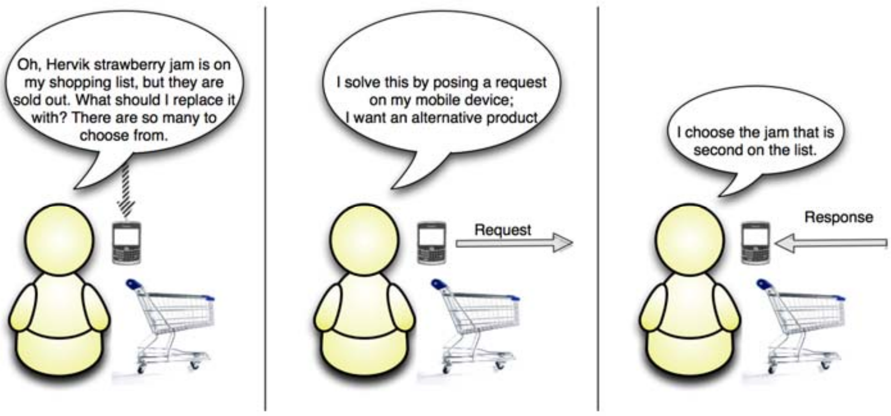

Fig. 1. Scenes from scenario – Request for alternative product

The result is delivered to Bill's device, and gives Bill information enough to make a well-founded choice. The rest of the alternatives have been excluded due to low relevance. Bill chooses the second alternative because he does not mind the additive potassium sorbate. The reason several alternatives are given is that the preferences only give an indication for what the system thinks can be most relevant, and there is not necessarily one correct answer. Presenting only one result could eliminate other relevant products. By presenting the most relevant ones and providing information about them, it is up to the user to make a final decision.

3 The Personal Profile and Food Ontology

Before we describe the ontology we will shortly describe the background for the process and how we have proceeded with the creation of the profile ontology.

3.1 Profile Information and the Process

Characteristics described in the personas are partly used for structuring. They give indications for necessary properties and classes, particularly with regards to personal information and stable interests. We also use the scenarios to extract information that is necessary or useful to achieve the personalisation we propose. To do this, the scenarios have been analysed in more detail with regards to the personalisation process. The scenarios also tell much about the stable and temporary interests.

Since the goal is not to create a complete profile, we focus on general concepts that make it possible to achieve the successful personalisation we aim for. Therefore, the profile will only consist of a portion of the information that should be part of a complete profile. The contents will be constrained by our scenarios, but could be extended to cover other areas and more details. Since many of terms that need to be modelled are more abstract than physical, effort to decide how to model it has been needed. This has also been an issue as to which classes that needs to be included and how they are to be related and modelled in relation to other classes.

Since we focus on mobile food shopping support we have limited the scope for the rest of the world that is modelled. We look at the food domain that can be related to local supermarkets in our neighbourhood. Figure 2 illustrates the top level of classes in the ontology, while Figure 3 illustrates top level relations. Some of these will be referred to in the examples. Many of the defined classes will not be mentioned since they are included for reasoning purposes related to useful classifications used in the personalisation process by the mediator. We focus on the classes that are relevant for the described persona and scenario in section 2, and which are used to define a person and related parts of the food domain.

The information in the personal profile can be divided in three main parts. The first category is termed personal information. Personal information consists of categories of information that is common for all users. Personal information is useful to identify the demographic properties of users. Many of these can be derived from the persona description. They change very seldom and typical examples are name, birth date and address. This type of information is particularly useful when connecting to a new service provider who is interested to know who you are and where you live or what your phone number is etc.

The second category is termed stable interests. It is called stable because the type of information does not change frequently, due to importance and relevance. Once a user has an interest, he is likely to have this interest for a longer time span, e.g. favour a specific producer of jam. The interest for this producer is the same from one week to another.

Sometimes it is useful to be able to specify interests or activities that do not last over a longer time span. Therefore, the third category is termed temporary interests. For a shorter time period a user could be interested in for example buying a new digital compact camera. In our case the daily shopping list represent the temporary interests. As soon as the goal is fulfilled, it is no longer part of the personal profile.

Fig. 2. Protégé class hierarchy

3.2 Describing Personal Information

The profile is centred around the *Person* class, which will be the main part with regards to representing an actual person. Bill will be represented as an instance of the *Person* class. The properties we have included to describe who a person is, are his name, his family relations etc. Some of the datatype properties included are *hasName* (type String), *hasAge* (type int), *hasBirthday* (type date) and the object properties *hasGender*, *hasFamilyRelations* with subpropeties *isMarriedTo* and *hasChild*. We have included properties for both age and birthday, so that we do not have to compute age. A person can be either a *Man* or a *Woman* (not both), and are connected through the *hasGender* relation. Many of the relations related to personal information correspond to relationships also modelled in GUMO+UbisWorld [10] and SUMO [11]. We have not used these unabrighted though, since an earlier analysis [12] has shown that existing ontologies in this area are not directly reusable.

The personal information part has not been very important in our scenarios, and therefore we only include basic personal information. This part can be extended as it in many situations is useful to exchange detailed and extensive personal information (address, account information, phone number etc.) in an easy and controllable way. Personal information is used in many situations, and in the connection to new service providers controlled exchange or shared access of personal information can be useful.

3.3 Describing Interests

Stable interests are the most important type of information as to being able to find out the relevance of a specific service or information, and to target services to individual users. All the different preferences for a person belong to this group.

Long-term interests are important, and from the persona and scenario we see that it is useful to be able to indicate relative interest. As we can se from the persona Bill, we want to be able to specify to what degree he prefers for example ecologically produced food and fair trade food. Many of such preferences of a person are regarding how good or how bad he prefers or likes something or not. Such value partitions in our model are intended to indicate that a specific relation can have different levels of intensity or degree. We have chosen to select levels corresponding to high, medium and low for the different gradings. We have modelled this as value partitions that later can be further subdivided if necessary. Our value partitions belong to the class *Modifiers*, and all the different modifiers are modelled as disjoint classes which exhaustively partition the parent class representing the feature. The class *Modifiers* has the subclasses *ADHDAdditiveAffinity*, *EcoAffinity*, *FairTadeAffinity* and *PriceSensitivity*. Class *EcoAffinity* is divided into subclasses *HighEcoAffinity*, *MediumEcoAffinity* and *LowEcoAffinity* and similar for the other affinities except *ADHDAdditiveAffinity*. *ADHDAdditiveAffinity* is a class that is included for being able to say that one avoids additives with a certain effect with regards to the medical diagnosis ADHD. Each modifier can be connected to the *Person* class through object properties *hasEcoAffinity* and similar for the other affinities. All affinity properties are subproperties of *hasAffintiy*. The combination of different affinities makes it possible to use them together in different ways in the search for relevant services, and this is done by the mediator during the personalisation process. A person having a high affinity for ecological products, would typically value products that are ecologically produced very positive. Someone not interested in ecological food would not indicate any interest related to ecological food, and hence the fact that a product is ecologically produced or not would not affect any possible rankings.

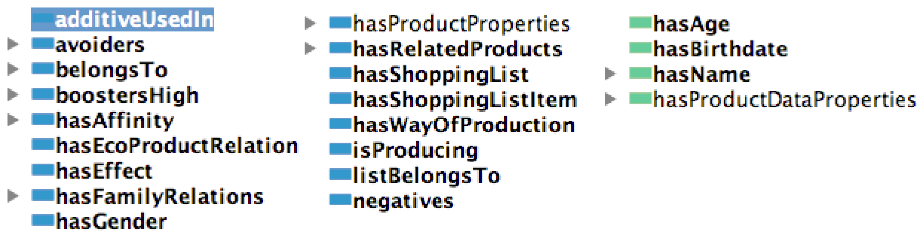

Fig. 3. Protégé top level object and data type property hierarchy

While many of the persona characteristics indicate what the personal information and the stable interests are, the shopping list indicates the father's and the household's temporary interests. Temporary interests are important to understand the particular situation the user is in and his needs at the moment. To make it possible for Bill to specify which items are on the shopping list, there is a class *ShoppingList*, where Bill's list can be registered. It can for example be the individual *BillsShoppingList*, which is a type of *ShoppingList*, that can be related to particular food and food products (e.g. Hervik Ecological strawberry jam) through the *shoppingListItem* property. When we know some characteristics of a person, it is possible to use this information to define new classes (e.g. class *EcoConcerenedPerson* which are all instances that are persons and have the affinity high for ecologically produced food).

3.4 Food and Related Concepts

In addition to representing people, there are classes that have been included to describe concepts about the food domain. For this we have used a public food taxonomy [13] for information about existing processed food and commodities. It seems that there is currently no complete overview of products and list of contents of products online. Therefore, the information about jams and its ingredients has been manually collected from the products' list of contents out in actual supermarkets. Due to the political focus on food-safety, it is not unlikely that such information will be made publically available in a digital form in the future. What we then need is to connect the information we have about food and the actual persons that are modelled in the *Person* class.

The main classes are *Food, FoodInformation* and *NonFood*. The class *Food* has been separated in *Commodity* and *ProcessedFood.* Class *Additives* is a subclass of *NonFood*. The class *Jam* is a subclass of *ProcessedFood*, which is a subclass of *Food*. The jam that Bill is looking for is typically an instance of one of *Jam's* subclasses *StrawberryJam*. We have named the instance *HervikStrawberryJam*.

FoodInformation has subclasses *Producer* and *QualityMark*. The class *Producer* represents all the different kinds of producers, e.g. like the ones producing jam in the scenario; *Nora*, *Ica* and *Hervik*. These are represented as individuals. Food can only be marked as E*cological* or *FairTrade,* which are the instances of *QualityMark*. Types of *Food* are connected to *Producer* through the properties *hasProducer*. Whether a product is ecologically produced or not, is specified through the property *hasQualityMark* (which is a subproperty of *hasProductProperties*). All products that have the quality mark ecological are considered ecologically produced food.

4 Overall Personalisation Architecture

Here we present the personal profile in relation to the other necessary components. The *mediator* is responsible for the personalisation and connects the right users with the right services. To do this, the mediator is provided the necessary parts of the profiles, information about the domain and devices etc. These sources of information are used in the different steps in the personalisation process. All the service agreements and searches for services (providers) are done through the mediator.

The process is initiated by the expression of a request which represents the user's goal in a particular situation (by user or service provider). The user poses such a request from his mobile device. The request starts the personalisation process performed by the mediator. The profile, which should be stored at a trusted third party, will be available in the process providing the mediator with relevant profile information. This profile information will be used together with the information about the domain, which in our case is about food and food products. The preferences in the profile are defined in relation to what information that is to be found about food, e.g. is a person's concern in ecological produced food related to the way the a particular product is produced. The main steps of the mediator as the matchmaker are pre-processing of goals, find services, compose services, adapt result to device and delivery. Several sources of available information are involved in the personalisation. External knowledge represents information sources that the mediator has access to, but not necessarily owns and administers. Where these sources of information are physically stored is not the focus of the current paper. The important thing here is the use of information, and the benefits gained in the personalisation in the form of relevant services. The real world is observed by sensors, and parts of it can be perceived and interpreted as context information. Context information can for example be a user's location, location of other users, the weather and time of the day.

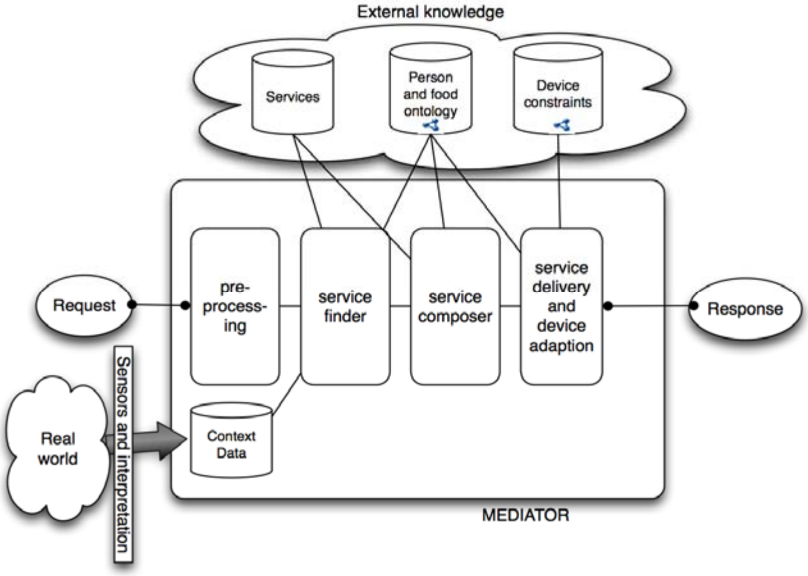

Fig. 4. Overall personalisation architecture

A user request represents an explicit need or goal of the user, and corresponds to pull services as the user is the active part. Requests are sent directly to the mediator which is responsible for the matching. In addition to explicit requests posed by users, it is also possible for the mediator to support users' implicit goals. Trying to satisfy a user's implicit goal correspond to push services, where the user is a passive part. In such cases the mediator is able to find matches between available services and users' profiles that match a particular service or group of people the provider is interested in. For both types of requests it is important that the response provides a result that is relevant for the user. In the presented scenario, Bill proposes an explicit request.

While the user perceives the personalisation process as one step with one input and one output, the mediator actually performs a set of steps to be able to return a response to the user according to the initial request. Hence, from the user's side, the communication with the mediator in the scenario will be perceived as a simple service that retrieves an alternative product based on the request he poses. Figure 4 illustrates the main steps in the personalisation process. However, in the steps of the personalisation process to produce relevant results for the user, the mediator in many cases executes more than one service to produce the result that is to be delivered. Non-functional requirements (performance, throughput, response time etc.) are also important, but our focus has been on the functionality that is to provide relevant services to the user.

When the mediator receives the request it has to do some pre-processing before the request can be handled. This depends on how the requests are expressed, and how they are going to be used in the search for alternative services. If several services are needed to fulfil the request, then the request needs to be split up in separate parts so that smaller services can be found. These parts will be called sub-requests. A request or sub-requests should make it possible to find services that imply the possibility of delivery of relevant results to the user.

After the request has been transformed, it will be used to search for services that can satisfy the request. It is necessary for the success of the personalisation that the services retrieved, which will lead to the delivered response, are relevant for the user. If more than one service can be considered relevant, the most relevant service should be selected. Services can be relevant at two levels. At the first level of the matching we are concerned with finding relevant services according to the request. In this matter a relevant service is a service that can satisfy the request fully or partially. On the next level we speak about the relevance of the result of the execution of a service. This is particularly useful when the service delivers multiple results. In cases where a service gives several results, it is necessary to chose one or more that are relevant to the user. To do this, personal information is an important factor to be able to decide what is relevant and how relevant it is. In this step, sorting of the information is important. Like in the presented scenario, several smaller services are necessary to produce a prioritised list of alternative jams, e.g. find all alternative products, find out to which degree a specific jam satisfy a user's preferences, sort alternatives by relevance.

When a service (or several services) has been found, it will be used to find or reason over information in the knowledge base. The selection of which information to be chosen to be a part of the result is influenced by this information. In some cases retrieved information needs to be ranked. Then the most relevant information should be selected to be a part of the delivery of the response. In the presented scenario the system actually finds ten different alternatives, but only presents a selection of the four most relevant results. Since devices have different abilities, the result should be adapted according to device specification. When the result has been set according to the user's device, it should be delivered to the user.

5 Related Work

The need for systems to adapt to their users has been recognised in many application areas. So far much focus has been with regards to applications intended for stationary computers. Personalisation for mobile systems has a different focus, where services and the control and automatic selection of services are important. For a mobile user it is essential to be in charge of the flow of information and services. Exactly what personalisation will mean for future mobile services and how it should be done is still more open. However, personalisation is a compelling feature for mobile communication systems for both end users and service providers. I the busy life of mobile users relevant services are important.

Originally user modelling techniques were restricted to desktop systems on stationary computers. Lately there has been an increase in ubiquity of mobile and embedded devices. Hence, it has become apparent that in many cases the recognition and modelling of the user's external context is essential [14]. Ontology based user modelling is a direction where ontologies are used to structure user models [15]. There have been several proposals with regards to models of users using ontologies. Some ontologies are described as personal profiles and are publicly available (for viewing and editing) and referenced in papers (e.g. [11], [16]). However, there are also many ontologies only described in papers (e.g. [17],[18],[19],[20]). A common feature is that most of the ontologies are built from scratch.

The field of user modelling is said to contribute significantly to the enhancement of the effectiveness and usability of ubiquitous computing systems. On the other side, the field of ubiquitous computing is building the technological basis for these systems. This new technological basis offers the user modelling community opportunities to apply their methods to new kinds of systems. The combination of user modelling and the technological basis of ubiquitous computing can contribute to extending the methods themselves in the process [14].

The biggest change regarding personalisation is the focus on a person as one individual, and not a heterogeneous group. Focusing on individuals, other factors than earlier can be relevant for the personalisation process. When one says that personalisation is concerned with tailoring specifically to one individual user, other factors than just the user will be relevant, e.g. the result of personalisation in different settings or contexts should differ.

6 Conclusion and Future Work

A world where people have the possibility to be connected to the Internet everywhere and anytime poses new challenges as how to provide relevant information and services to mobile users. Today users have no way of controlling and providing necessary information that can improve the quality of services they receive. Personalisation by the use of personal and contextual information is what we propose to improve the situation and open up for new possibilities for users and service providers.

When mobile personalisation is successful, it can lead to several positive effects. Service providers can personalise services according to user needs and interests to reach the right customers, and users can receive services and information that actually is relevant. An effect of relevant services and information can be a wish to be loyal to the provider (lock-on). On the opposite we have lock-in, which can be characterised as a situation where the effort of changing provider exceeds the advantages of the change of provider. Sharing of information between users and providers can lead to an increase of trust when the information leads to delivery of relevant services for the user.

Personas and scenarios have worked well in the process of visualising the personalisation process, and the use of the actual profile information. In addition to understanding the steps in the process, the personas and scenarios have been useful in the modelling of the profile. The information in the profile is an important factor when the personalisation is to rank different alternatives available and for exchanging personal information, for example when joining a new social community. From the simple scenario presented here we see the benefits the father achieves by having shared his profile information. He receives a list of relevant strawberry jams available, and can by himself make a choice of which one to buy.

In addition to physical concepts, it is necessary to also include abstract concepts that need to be modelled in a logical way. Therefore, building a personal profile was challenging. Several solutions of modelling a profile are possible. Since many different types of information about a person can be included, we have used personas and scenarios to limit the scope. The profile has been created to cover the areas of developed personas and scenarios. For the creation of the profile, the parts related to food and food products have been the easiest to model as they are physical concepts. Since many of the personal information relations are so similar in many areas, they were also ok to model, especially since we only included the most basic information. It was challenging to represent what we have termed stable and temporary interests, and decide how they were to be related to the actual food product so that relevance could be computed. Logical class names and names of relations are more troublesome to define, and at the same time one has to comply with the ontology language and tool. Several iterations have been necessary.

The ontology in OWL DL is used in a prototype which uses OWL API [21] and the reasoner Pellet [22] for inference, where the information in the ontology is used in the personalisation process. The overall goal is to show that successful personalisation can be enabled where the user is provided with relevant services that are targeted particularly for him that is suitable in the situation the user is in. We believe this can be achieved by the combination of personal and contextual information. The developed scenarios will be used for the evaluation of the personalisation proposed and its success. The implementation will be evaluated according to developed personas and scenarios. In addition, the personalisation concepts will be tested using mock-ups with test people through the RECORD Living Lab [23].

For future use, it can be feasible to combine manual maintenance of the personal profile with automatic building and adaption of profile information (e.g. through analysis of what a person or family actually buys, or through opinion mining finding identifying products with a lot of positive or negative mentionings). When other people’s opinions are to be considered, the opinions of like-minded people should be more valued than general opinions, and such are typically to find in communities with similarly disposed persons.

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Beyond life streams: activities and intentions for managing personal digital memories

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Abstract. In this paper, we expose a set of initial ideas related to an innovative way of structuring and organizing personal information. Indeed, users have to deal with a huge amount of information either coming from social connections, collected on the Web or generated by them. This phenomenon leads to new research challenges. In particular, how to structure, organize, and classify this personal information in order to *better manage the user's digital memory*? In this position paper, we present the concepts of activities and intentions as means for the user to structure efficiently all his past information, but also help him in the future, for example by suggesting relevant events, anticipating his information needs or providing opportunities to satisfy latent desires.

Keywords: personal information management, digital memory, timeline, activities, intentions, information container, anticipation of information needs

1 Introduction

Nowadays, due to the increasing development of communication technologies, social media, massive content production or diversification of knowledge sources, users tend to be overwhelmed with a huge volume of personal information such as emails, photos, e-books, blogs, social feeds, or various documents. These data are either created by them (e.g. through lifestream aggregators such as FriendFeed[1], Lifestrea.ms[2], etc.) or by others (e.g. through social services such as Twitter, Facebook). All this information are from near or far sighted centered on the user life - social exchanges, information gathered on the web, etc. and constitute what we call the *user's digital memory*.

However, today this information is only captured, stored, but not very-well organized from users' point of view and thus is not used as much as it could be. This phenomenon induces the following research challenges. First, how to keep track of important events? Which semantic structure would allow users to find the right information when needed and *organize their digital memory* properly? A second

[1] http://friendfeed.com/
[2] http://lifestrea.ms

challenge deals with the anticipation of information needs: we believe that a user-centric semantic organization of the digital memory may help the user in his current or future information needs.

Thus, we present some initial ideas towards a new way of indexing and structuring users' digital memories. Section 2 gives an overview of existing models and solutions for managing personal information. Section 3 introduces the notion of *activity* as a key concept to structure personal memory. Section 4 gives some clues on how to go beyond this first layer, by enriching this semantic structure with an additional meta-layer of information organization, based on the notion of *intention*. Section 5 illustrates how this intention-based personal information management model can be instantiated for improving content filtering and opportunistic recommendations.

2 Related art

The problem of organizing and structuring personal information is not new. This field has already been studied in the domain of personal information management, and several paradigms of document organization have been identified. Temporal paradigms organize documents according to a time line. This is the way how life streams[3] [4] are usually presented to the user. Life logs projects such as Microsoft MyLifeBits [6] aim at storing in a database a massive set of every activity and relationship a person engages in (books, music, photos, video, office documents, email, phone calls, meeting, web pages, etc.) and structure them according to two axes: time and life (personal vs. professional). However, according to Gemmel, "the collection is so large that the user cannot remember much of the contents, and will never *use* them." Some solutions use a spatial representation, such as in Data Mountain [3], a logical paradigm, based on keyword or content assignment, such as in Haystack [8], or a combination of dimensions such as TimeScape [10]. Search engines such as Google Desktop[4] are an alternative to structured information, but in the case of digital memory, they do not rely on an index with the right granularity from the user's point of view. Other approaches propose manual ways of structuring information. For example, Pearltrees[5] proposes to users a way to keep content they find everyday on the web and to let them structure their information through trees.

Finally, some research has been carried out in the perspective of anticipating information needs. Thus PackHunter [5] is a collaborative tool to share with a group of users web trails, which allow jumping to pages visited by others, etc.

However existing work are limited to an organization through a structure (e.g. timeline, hierarchical) with limited semantics which does not correspond effectively to the way users behave. So, there is a need to better structure this digital memory to make it useful and usable to the user. In this paper, we propose a solution using episodic memory [12] with two different layers: *activities* of the user and his *intentions*. We detail these concepts in the following sections.

[3] Cf. http://www.readwriteweb.com/archives/35_lifestreamin_apps.php for examples
[4] http://desktop.google.com
[5] http://www.pearltrees.com

3 Activity-based personal information management

In the human memory process, two main steps are fundamental: the *acquisition* (retention) and *recall*. Tulving in [12] showed that episodic memory, which receives and stores information about temporally-dated episodes and spatio-temporal relations among them, is a faithful record of a person's experience. Recalling a piece of information is easier when the user can remind himself in time and space. Besides, according to a recent study [1], users tend to think about and classify their personal information in terms of activities more than they do in terms of information type or just time. The positioning of information in a three dimension space (time, place and people) is already envisioned as a de facto standard to structure life logs [2]. Activities are adding to the event notion a semantic context, which defines another essential dimension for representing the user's daily life. Therefore, they may constitute a good paradigm to manage digital memory.

Thus, we can think of organizing user activities in a temporal way through a timeline of activities. This organization shows how activities can also address different research areas in the domain of multimedia content consumption according to their position in the timeline.

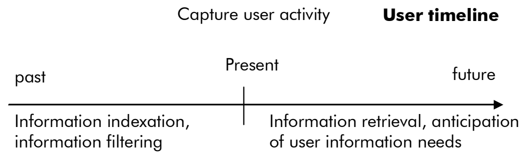

Figure 1. Usage of the activity concept in the user timeline

As presented in Fig. 1, the "present" part of the timeline consists in capturing the current user activity. Capturing user activity is a research area in itself, where different related work [13] could be used. The "past" side of the timeline enables to index content and people and keep track of user memory. Past activities are reference marks (i.e. episodes) for people to find information and content, and a support for social information sharing even after their end.

More formally, we define an *activity* as a personal activity (digital or not) or as a user's perception of a given social activity or event. Based on this definition examples of activity can be: reading a book and making notes and comments, or meeting someone in a conference and exchanging information, collecting multimedia content related to a user activity. An activity is composed of the following main properties:

- *A set of content* that the user has generated, consumed or bookmarked in the context of the activity. A consumed content can be any type of multimedia content or web bookmarks. A user generated content can be an important piece of information written about the user activity (document, comments and annotations, notes) or any interaction captured during the activity (phone call, IM, email, chat, or interactions through social media applications).
- *A semantic context* is inferred from the set of content. It is a key enabler for the awareness of the activity community, and for further information classification.
- *A social context* of the activity is the list of people that are sharing this activity (implicitly people around the user), or people following this activity (explicitly

defined by the user or gathered from interaction traces related to the activity semantic context).

- *A spatio-temporal context* of the activity. Time and place are the two dimensions that can be used to identify typical user contexts such as “at home”, “at work”, “on the move” or simply to position the activity in space and time for a better user recall.
- *A status*. An activity can have three distinct statuses: ended, ongoing and in mind. The *ended* status means that the activity belongs to the past and that it can be used as a piece of memory. An *ongoing* activity constitutes a recipient for new incoming information. An *in mind* activity is not yet started; this is used to describe latent activities that may be recommended in the future to the user.

The role of the activity is twofold: (1) a working space environment where all pieces of information (documents, emails, bookmarks, etc.) and pertinent contacts are gathered within a same structure, becoming a relevant index (on people and content) for structuring the user digital memory, and (2) a representation of the social environment of an activity, helping people to share information in a controlled way and to get information from their social networks around this activity.

4 Intention-based personal information management

The management of personal information through the notion of *activity* provides already a first organization layer. However, it does not consider interdependencies between activities. So, we propose to extend this semantic structure with the concept of *information container* as a semantic entity that encapsulates a set of coherent activities that are correlated according to the different activity dimensions. Ultimately, the observation of correlated activities may denote user’s *intentions* in time and space, that describe what the user wishes to achieve at a high and pragmatic level [9].

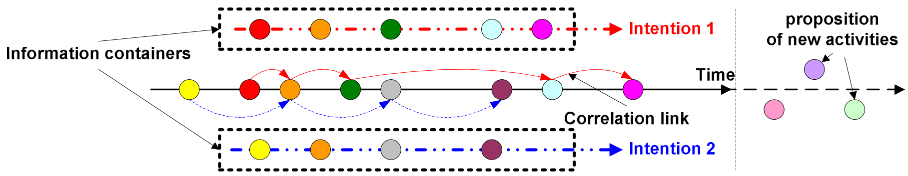

Figure 2. Notions of information container and intentions

The “past activities” of the user (Fig. 1) are structured through an additional layer, an *information container* (Fig. 2). The latter is composed of a *set of activities* and one or several properties describing the nature of the correlations between activities:

- A *content link* reflects the shared semantic context between all the activities;
- A *social link* contains the common contacts or social context (family, colleagues, etc.) between the activities;
- A *logical link* indicates how an activity relates to others. Possible links are *causality* (an activity is the follow-up of another one), *temporality* (an activity is the repetition of another one), etc.

Based on the analysis of these semantic links an *intentional link* can be inferred between the activities present in a given information container. An *intention* can be seen as the high level "glue" between several activities and describes the set of activities as a whole unit as in [11]. Contrary to previous works such as [14], we do not express an intention by a formal plan; nevertheless at a high level, it may be described thanks to an action verb, a complement and an intensity reflecting its certainty or feasibility.

In addition to its structuring role of past activities, the information container can be seen as an *active* recipient, in charge of helping the user towards the "future" side of the timeline (Fig. 1). Indeed, intentions act as a guideline that leads the user involvement through various activities. Thus, the knowledge of existing intentions can be used to recommend information associated to activities belonging to the container or which are completely new for the user. Additional exploitations of intentions can be envisaged through some forms of collaborative mechanisms for different purposes, for example: 1) to enrich / suggest activities to a user based on the detection of a common activity pattern with other users – this may help the user to find faster what he needs; and 2) to build a dynamic social network around people having a common intention, in order e.g. to help them to realize it jointly [7].

Moreover, an information container is not static, it may grow by acting as a kind of agent that enriches the information it contains with coherent new elements coming from specified *information streams* (email, IM, RSS feeds, notifications etc.).

The iPIM ontology (Fig. 3) describes more formally the concepts described above.

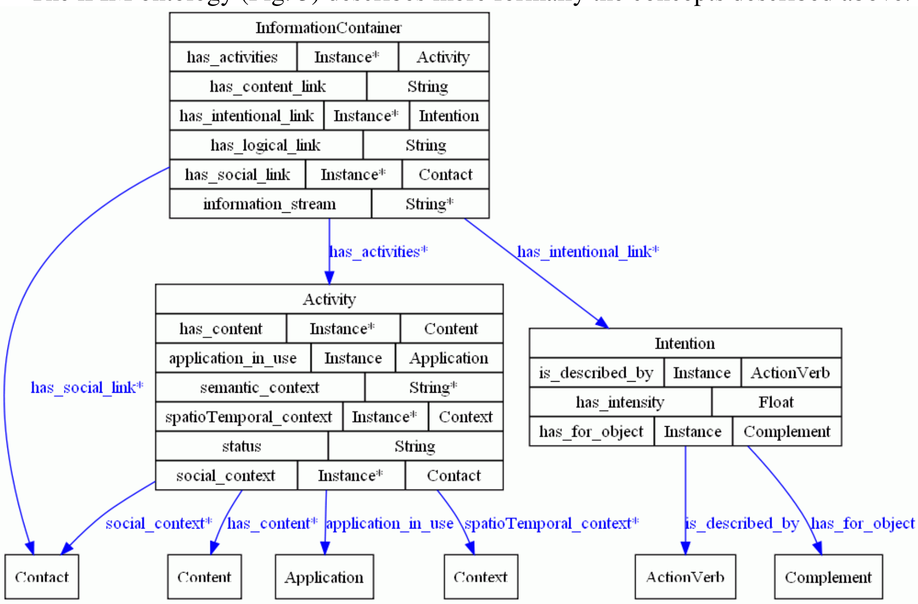

Figure 3. Overview of the iPIM ontology

This vision raises many research questions:

– *Construction of information containers*: how to correlate activities to build those information containers? When a new activity appears, to which information containers should it belong to? Is it just a clustering problem? How are we able to modify the information containers if we detect an anomaly?

- *Identification of intentions*: detection of a precise user intention may be difficult. A possible solution is to use a learning model, where the user at the beginning explicitly describes the intention associated to an information container. After a while, the model could suggest the user relevant action verbs and extract knowledge from social and/or content links as complements. Another possibility would be to use a collaborative model which compares information containers of one user to the ones of other users to suggest possible intention labels.
- *Monitoring of intentions*: how to infer the progress with respect to an intention or an information container?
- *Usage and acceptance* – how to capture or confirm user activities (what is the part of automation and manual declaration) and present information containers to users?

5 Exploitation of iPIM to improve recommendations

In this section, we express through a scenario how the semantic structure described above can be used, in particular as a way to go beyond classical recommendation systems. Fig. 4 summarizes the different user's activities that occur during the scenario. This scenario shows how a system can monitor in real-time different user's activities, such as watching a documentary, browsing the web, meeting friends, etc. and the nature of the resulting intentions over the time.

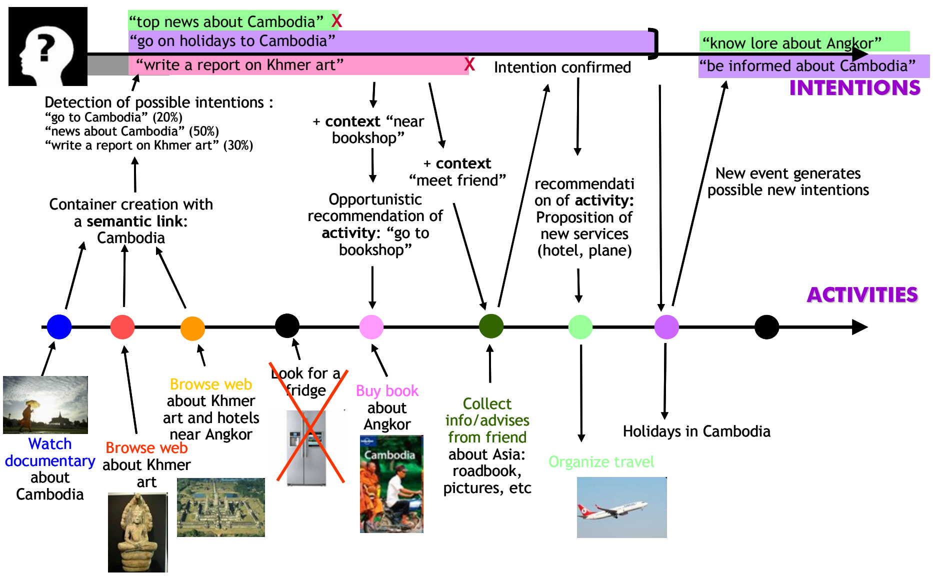

Figure 4. Illustrative scenario

The scenario can be decomposed through three main axes:

- *Activity indexing*: from the user timeline several *activities* are detected and then indexed by the system based on their *contexts* (e.g. for the activity "watch a documentary" the *semantic context* is a documentary reference and its *status* is equal to ended).

- *Building of information containers*: in the scenario the construction of the *information container* is quite easy as most of the activities share at least the same *content link* related to Cambodia (except the "search of a new fridge"). By correlating more precisely the existing activities with past activities from other users (based on a collaborative approach) a *logical link* can also be inferred from the same information container (e.g. travel booking).
- *Intention detection*: within the Cambodia information container several user's *intentions* may be inferred based on the underlying information container links. For each intention the system tries to formalize its meaning (e.g. verb + complement form). In addition to the previous treatment a certainty degree is computed reflecting the current intention relevance according to several parameters (context, activities, etc). While new activities appear, the potential intentions are refined or simply removed from their information container. Thus, in Fig. 4, at the beginning three intentions were inferred, and at the end only one seems to be relevant: "go on holidays to Cambodia". Nevertheless first inferences are already useful for proposing relevant content or services – especially in an opportunistic way, where the user may not have thought about himself (e.g. meet a friend). Another interesting property of an information container is that even if an intention is ended (e.g. the holidays are now finished) it is still open to new activities; thus new intentions can emerged (e.g. know more about Angkor).

6 Conclusions and perspectives

In this paper we presented initial steps towards a new paradigm for structuring and organizing personal information. We believe that the concept of intention provides a relevant conceptual framework to anticipate user information needs, and opens the way to new service opportunities for context-aware multimedia content access and delivery. However we still need to understand if semantic and social contexts are appropriate indicators of relationships between activities to deduce user intentions. This can be learnt through a diary study, and further with experimentations on real captured activities. This new way of managing personal information may have a real social impact, e.g. by providing opportunistic interaction with people driven by intentions. To go a step further in the social exploitation, we envisage the use of collaborative algorithms for better inferring intentions through the co-relation of activities.

Besides, intentions could generate spontaneous social networks, i.e. communities of people sharing the same kind of intentions, which will ease social interactions, and help them collectively find the right path to fulfil it (joint realisation of an intention). A further perspective of this work could be the creation of communities of knowledge, based on people promoting their information container, and sharing with the community the solution they found. We could capitalize on this community of knowledge to identify similar patterns of activities to fulfil typical intentions, and propose appropriate compositions of services that can be seen as an intention-based service mash-up.

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R3 - A Related Resource Recommender

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Abstract. Due to the ever growing amount of content in the Web of Data, the retrieval of relevant information is challenging. Currently, efficient resource recommendation methods are lacking, that could ease the exploration of data in the Web of Data. To alleviate this situation, this paper proposes the R3 resource recommendation framework for retrieval of data in the Linked Open Data (LOD) cloud. It analyses relevant search engines and interlinking frameworks and, based on that, proposes the R3 framework which is illustrated both in theoretical and practical details. The framework enables the recommendation of (RDF) resources from the LOD cloud based on textual, structural, or semantic similarity.

1 Introduction

The goal of Linking Open Data (LOD) community is to bootstrap the Semantic Web (the "Web of Data") by publishing and interconnecting datasets using RDF[1]. The outcome of this movement is the so called LOD cloud which grew to 13.1 billion triples and 142 million RDF links in the last two years and it is still growing [2].
As within the traditional, document-centric Web, search and retrieval of information is of utmost importance. Similarly, a big challenge for a specific end user or application, operating on the Web of Data, is to find relevant data that serves their specific needs. Despite the fact, that Linked Data browsers and search engines are available to explore content in the LOD cloud, means to issue complex queries by ordinary users or to recommend content in the cloud based on particular interests, are currently lacking. In case a user is searching for the city of Berlin using a LOD search engine, he is able to retrieve resources with many properties such as their names, descriptions, latitude, longitude, or density of population. If she now would like to retrieve related resources such as a ranked list of cities ordered by geographical distance and/or density of population or resources with similar structure (like countries or provinces) ranked on the semantic similarity of their textual description, she will fail with current search engines. Similarly the recommendation of related resources could allow the user to issue a "Query by Example" by defining some kind of a fake-resource and use it as query base, which would be a novel form for searching the Web of Data.

In order to alleviate this situation, this paper investigates the state of the art in LOD search engines and interlinking frameworks (Section 2) and, based on that, proposes the R3 resource recommendation framework that is capable of recommending data from the LOD cloud based on the semantic, structural, or textual similarity of given resources. The framework allows to query for related things in the LOD cloud based on a given resource and is illustrated including its requirements, conceptual architecture, and implementation aspects (Section 3). Finally, details are given on how to further advance and implement the framework (Section 4).

2 Resource Discovery and Interlinking in the LOD Cloud

There are some applications on the web, which allow the user to search or browse the web of data. Supplementary to that there are so called Interlinking Frameworks that can be used to check the resources of two or more different datasets pairwise for similarity. Because of the analogies to our approach these frameworks should also be considered in the following discussion.

2.1 Browsers and Search Engines

Sindice[1], as described in [3], is a scalable index of the Semantic Web. It crawls the Web for RDF Documents and Microformats and indexes resulting resource URIs, Inverse Functional Properties (IFPs) and keywords. A human user can access these documents through a simple user interface, based on indexes mentioned above.
Sigma[2] is rather a semantic information mashup enabled by Sindice than a self-contained semantic search service. Nevertheless it enriches a lot of its functionalities with some nice additional features. It works as Web of Data browser where the user can start from any entity (found by a fulltext search) and then browse to the resulting page. The resources index is build out of from sites which use RDF, RDFa or Microformats.
The Open Link Search[3] will list entities with a user-defined text pattern occurring in any literal property value or label. It also supports Entity URI lookup. The Search can be redefined by filtering type, property value, etc.
It is also possible to execute SPARQL queries by using the SPARQL endpoint. Some demo queries are predefined and can easily be altered via text input fields.
Falcons[4] is described in [5] as a service for searching and browsing entities on the Semantic Web. It is a keyword-based search engine for the Semantic Web URIs and provides different query types for object, concept and document search.
Falcons also gives the facility of facetting over types by dynamically recommending ontologies. The recommendation is based on a combination of the TF-IDF technique and the popularity of ontologies.

[1] `http://sindice.com/`
[2] `http://sig.ma/`
[3] `http://lod.openlinksw.com/`
[4] `http://iws.seu.edu.cn/services/falcons/objectsearch/index.jsp`

Watson[5] offers keyword based querying to obtain a URI-list of semantic documents in which the keywords appear as identifiers or in literals of classes, properties, and individual. Search options make it possible to restrict the search space to particular types of entities (classes, properties or individuals) and to particular elements within the entities (e.g. local name, label, comment).
SWSE[6] is a search engine for the RDF Web. Similar search engines currently provided for the HTML Web it looks like a ordinary fulltext search. But the information retrieval capabilities of SWSE are much more powerful because of the inherent semantics of RDF and other Semantic Web languages.
Swoogle[7] allows a user to search through ontologies, instance data, and terms of the Semantic Web. Furthermore it supports browsing the Web of Data. This search engine also uses an archive functionality to identify and provide different versions of Semantic Web documents.

Like described above, each considered semantic search service provides a certain amount of functionalities. Some of them are part of two or more services, others are exclusive to one certain engine. Though it is possible to search for appearance of a given resource in some of them, neither it is possible to find related resources for a resource and its RDF triples nor to define on which triples the relationship should be calculated on. Also the search engines do not consider a semantic similarity of queries and content, which definitely could increase the quality of result. But there are applications in the area of Semantic Web which match some of these requirements in certain ways - the interlinking frameworks.

2.2 Interlinking frameworks

Interlinking frameworks for semantic web data try to detect related and link resources in different datasets. In [8] several frameworks are compared to each other concerning their functionalities, which brings us to the decision that the Silk[8] approach is rather related to our goals.
Silk[7] is a framework for detecting explicit RDF links between data items within different data sources. Using the declarative Silk - Link Specification Language (Silk-LSL), developers can specify which types of RDF links should be discovered between data sources and, based on arbitrary metrics and aggregation functions, which resources should be declared as related. Silk accesses the interlinking candidates via the SPARQL protocol.
The usage of different metrics and aggregation functions for different types of properties can be adopted to our resource recommender. In addition we can remodel Silk-LSL in some ways (e.g. alternative metrics) and use it as query syntax. This language makes it also possible to define the appropriated datasources by query.

[5] `http://kmi-web05.open.ac.uk/WatsonWUI/`
[6] `http://swse.deri.org/`
[7] `http://swoogle.umbc.edu/`
[8] `http://www4.wiwiss.fu-berlin.de/bizer/silk/spec/`

3 R3 - A Conceptual Overview

Our intent is to build a recommender service, which allows to query for related resources from various (predefined) datasources based on a given resource. But what is relatedness, what factors have an impact on it and how can we implement such a recommender service? This is discussed in the following sections.

3.1 Requirements

In case of RDF resources there are various factors which define relatedness. On the one hand the RDF structure itself (predicates and non-literal objects) reveals something about how similar two resources are. On the other hand the literal properties can be compared according to their types towards different metrics. That can be simple ones like euclidean metric for numbers, or more complex like semantic similarity of texts. A user should be able to specify the factors that are used to find relevant related resources, and also its impact on the result. In addition to that the whole recommendation process should be calculated in an adequate time. So we can specify requirements below:

1. Recommend related resources from the LOD cloud based on a given RDF resource.
2. Consider semantic similarity of texts and structural similarity of resources.
3. Offer a comparison mechanism for literals with adjustable metrics.
4. Allow user defined feature boost; that means a certain feature (e.g. property x or structure) has a higher relevance on relatedness than others.
5. Return related resources ordered by relevance.

3.2 Conceptual Architecture

The concept to fulfill these requirements is illustrated in Figure 1. The data must be fetched from the LOD cloud, combined and indexed; it should be queryable via a specific search syntax. This process is described more precisely in this section.

Data Consolidation
The service gets recommendable resources out of the Linked Data Cloud. Since it should possible, to build a multi-source index, there must be a kind of ontology alignment. Thus preprocessed data is stored directly into the index. The single datasources must be reindexed in given time intervals.

Resource Recommender Index
A core index can provide lot of metrics like euclidean distance, date similarity, string equality, etc. Semantic similarity which can be used to evaluate the semantic distance of texts and RDF structures is more complex, therefore we need a supplemental semantic index. Semantic textual indices (one for each defined property) as well as the semantic structure index (one for the whole dataset) are

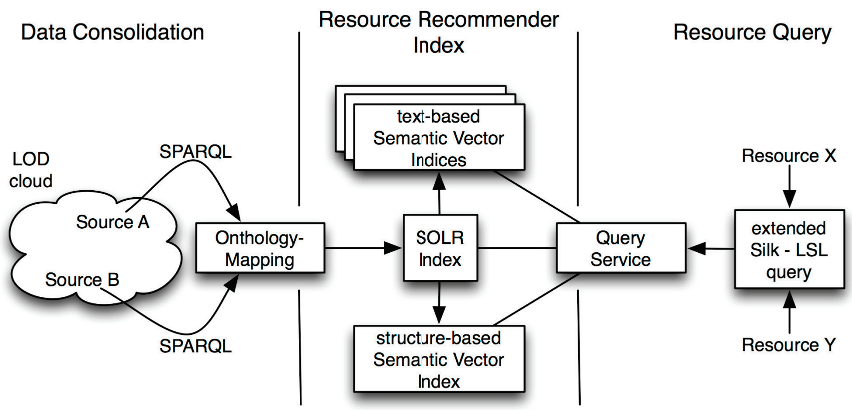

Fig. 1: Design and workflow of R3

build out of the core index.

Resource Query
To get recommended resources based on a given one, the recommender provides a query language, whereby the user can specify, which features should be included in the calculation according to which metric. Furthermore the factor how intensive a specific feature impacts the result and how the diverse values are combined is configurable by query. To restrict the set of base resources the user can define the included datasets. The searchresult is list of resources ranked by relevance.

3.3 Implementation

Datasets, which build our resources base is taken out from the LOD cloud via SPARQL. To map different resources from sources we use a simple mapping table. Complex ontology matching strategies like in [9] are also possible.
Because of its high scalability, its fast query processing and the possibility to use integrated functions and numerical as well as token-based comparison, we decided to use SOLR[9] as our index base. A lot of metrics like euclidean distance, date similarity, string equality, etc. are provided by or can be directly integrated into SOLR index. As described, for more complex metrics we need supplemental semantic indices build out of the SOLR index.

Text-based Semantic Index
A potential semantic index can be a Semantic Vector Index. This approach bases upon the Vector Space Model wherein every document is represented as a vector in an n-dimensional term space according to appearing terms. The Semantic

[9] `http://lucene.apache.org/solr/`

Vector Package[10] is able to build such an Index (which can be queried for semantic related documents) out of the basic Lucene Index.

Structure-based Semantic Index
The semantic vector index can also be used to index the semantic similarity of RDF structures. Therefore not every word or text module is integrated in the term model but the URI, RDF predicates and non-literal objects of a resource. Figure 2 shows the semantic similarity of a subset of dbpedia resources. To illustrate this semantic space we build a structure distance matrix of this resources and scaled it to two dimensions using classical multidimensional scaling (MDS) offered by the R statistics software[11]. We highlighted resources of different types which shows that related resources have a similar RDF structure.

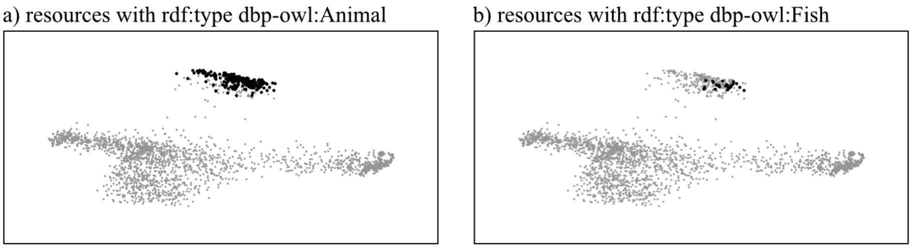

Fig. 2: Evaluation of Structure Index

Query Language
As mentioned, the SILK Link Specification Language[12] can be used as inspiration for a query format that fulfills our query requirements and allows to specify the basic resource (set of RDF triples or URI), the considered datasets (SPARQL endpoints used from data consolidator), relevant features and its impact and the applied metrics (taken from a fix set). Figure 3 shows an simple query example.

4 Further Work

In this paper we described the conceptual architecture of a resource recommendation framework for the Semantic Web. Our future work includes the implementation of this concept and a practical evaluation with real datasets. In a further step we plan to optimize the Semantic Vector package, which is used in one core

[10] http://code.google.com/p/semanticvectors/
[11] http://www.r-project.org/
[12] http://www4.wiwiss.fu-berlin.de/bizer/silk/spec/#specification

```
<ABC>
  <DataSource>
    <EndpointURI>http://dbpedia.org/sparql</EndpointURI>
  </Datasource>
  <Query>
    <Resource>
      <URI src="http://myhost/resource/a" />
    </Resource>
      <Condition>
        <AVG>
          <Compare type="structure"/>
          <Compare type="predicate">
            <MAX>
              <URI metric="semanticVectors" weight="0.7">
                 http://dbpedia.org/property/abstract
              </URI>
              <URI metric="numSimilarity">
                http://dbpedia.org/property/population
              </URI>
            <MAX>
          </Compare>
        </AVG>
      </Condition>
    <Limit>10</Limit>
  </Query>
</ABC>
```

datasource for recommendations

basic resource

calculation mode

weighted factors for relatedness (structure and 2 predicates)

other specifications

Fig. 3: Sample for a Recommander Query

component of the framework, to enhance its scalability and performance. The resulting recommender will be integrated into the KiWi[13] system.

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Introduction to Fuzzy-Ontological Context-Aware Recommendations in Mobile Environments

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Abstract. In the framework of context-awareness in mobile networks, handling both user and context in a homogeneous way is a key concern. It is particularly important in a recommendation process where imprecise user-defined values are compared with sensor inputs. This paper reports work in progress towards the realisation of a common representation framework for context- and user-related data, investigating the coupling of fuzzy theory and semantic web to deal with uncertainties and imprecisions issues faced by context-aware recommender systems in mobile environments. We propose a model allowing to represent ontology properties values as fuzzy sets linked with linguistic values. This model, pluggable onto any ontology, is meant in particular to be associated to context and user ontologies with the objective of enhancing context-aware recommendations quality.

1 Introduction

The mobile computing domain is still a wide field of study comprising lots of issues related, e.g., to the number and heterogeneity of networks, protocols, devices and communication interfaces of applications. While it is an inherent need for devices and applications in such an environment, bringing context-awareness in mobile networks remains an open problem. In our research work, we focus on problems related to context-awareness in hybrid networks, a class of mobile ad-hoc networks where nodes can be mobile or fixed [7]. This kind of network handles naturally social interactions since mobile end-users, through their devices, are seen as an integral part of the network in the form of mobile nodes. However, their inherent complexity makes them difficult to use when wanting to make applications context-aware: networks and information available to a user can be different at each moment, and so is it for information routing.

Fulfilling the needs of the end-user by providing targeted information and services in a seamless way, requires context-awareness to be also focused on the user profile and his preferences. In other words, this requires context-aware (and user-aware) recommendations. The state of the art shows however that context-aware research has focused more on sensors than on users [8], while in the personalization community, most of existing recommender systems does not fully consider context information [19]. This suggests open issues, that we would like to address.

Assuming that network availability and routing issues are solved at the network level, systems recommending information, content or services, designed for the web can still be used or adapted without heavy modifications. For example, a service-oriented approach for recommendations in the TV domain has been recently successfully applied in a mobile environment [11]. Indeed, when recommendation exploits only user profiles and occurs in the closed world formed by a provider and his customers, manipulated data are well formalized and adapted for the recommendation process. In this case, data sources are known and de-facto reliable. However when wanting to take the context into account, the multiplicity and heterogeneity of data sources must be considered. In mobile environments, context information sources include physical sensors as well as abstract ones like, e.g., web services or human-originated information. Issues related to Information Quality (IQ) arise, such as completeness, precision, currentness, provenance and trustworthiness [18] [20]. This becomes especially true when users themselves become (context) information providers through ad-hoc networks formed by their mobile devices. Like when expressing their preferences, information provided by users is often approximated or incomplete, and inherently fuzzy.

Context data sources heterogeneity induces interoperability issues, some of which can be solved using the common representation framework provided by ontologies [2]. But this allows only representing context data using a common vocabulary and concepts having a well defined semantics. While this brings a very good support for reasoning, limitations also exist, especially regarding uncertainty and imprecision. In the Semantic Web community, this has lead to research works on the joint use of Fuzzy Logic [23] and Semantic Web [15]. Regarding IQ issues on context data, the fuzzy theory could provide at least a partial answer. Indeed, it offers a framework to represent partial truth and imprecise valuations such as those represented with linguistic variables, and allows for approximate reasoning.

In order to set-up a common representation and reasoning framework, we investigate the coupling of fuzzy theory and semantic web for context-aware recommendations. Our main goal is to propose ontology-based models and algorithms grounded in fuzzy theory to deal with uncertainties in human related assumptions, confidence in predicted data, and management of trust, and more generally providing a framework for reliable context data whatever its kind and origin. In this paper, we first discuss briefly the handling of context and related quality issues in mobile environments (section 2). Then, as a first step towards the realization of our framework, we focus on the coupling of fuzzy sets and ontologies for modelling vague human-related data together with other machine-originated context data like, e.g., those provided by sensors. To this end, we propose in section 3 a model allowing to use fuzzy sets in ontologies and explain how it can be used to model contextual information. Section 4 concludes, relating to other similar works and brings some perspectives and future works.

2 Handling context in mobile environments

2.1 Context gathering processes

As suggested in the introduction, making recommendations in mobile environments cannot be achieved by only taking into account the user profile and preferences. Mobility implies considering contextual information concerning the user himself and his environment, but also the networks availability and physical constraints limitations, as well as any useful environmental and situational information. Achieving true context-aware recommendations bears some issues. According to [22], current approaches for bringing context-awareness to personalisation systems suffer from accuracy and reliability problems. User preferences and interests are indeed context-dependent and only few approaches try to take it into account, especially in an evolving context [12].

Personalised context-aware information delivery in mobile networks depends on a series of data gathering and aggregation processes, each being followed by a processing and analysis phase leading to adapt or recommend an item. These processes are related to the user and his context, the resources to be delivered, and the network:

- User profile building: the explicit user profile (containing characteristics like, e.g., demographic data) is completed with an implicit part that is inferred from the user behaviour. To be actually reliable, implicit profiling needs to consider user consumption or action context.
- Aggregation of user context: gathered from sensors surrounding the user or able to provide any relevant information about the user situation, but some elements could also be inferred from user behaviour (e.g. for determining mood or activity).
- Aggregation of data concerning the network properties and state to anticipate the Quality Of Service.
- Aggregation of data related to the information or resource to be transmitted: its source, its characteristics, its intended target, etc.

2.2 Context quality issues

Each of the above listed aggregation processes leads to implement dedicated interpretation and conversion methods. The latter bear some risks that are related to Information Quality (IQ). As suggested in [19], these risks can significantly impact the usability of profiles for personalized applications. The quality of context information is influenced by different factors from the network layer to the end-user application: data availability, completeness and reliability; data sources trustworthiness; transport reliability (data loss can occur in the network); aggregation reliability (including homogenization of data and conflict handling). Additionally, information can be irrelevant if used in a non-suitable context, or become obsolete over time. As emphasized by [18], IQ is sensitive to context changes, such as time and usage goal. A sensor could loose precision when it rains. A user preference can be misinterpreted in an improper context (e.g. "John Doe prefers to see action movies on weekends" [19].

In order to assess the quality and thus usability of aggregated information during a context retrieval phase, it is necessary to consider IQ-related issues and in particular the validity of each data regarding the context. A context layer must be added to the models used for personalization, not only to represent the current user context but also to identify the items which can be delivered in an optimal way given a specific context, and the dependence of user interests and preferences in context.

The particular IQ issue on which we focus here concerns data precision and completeness. In our mobile environment, information providers include digital sensors as well as humans. They provide data using different formalisms and influenced by different factors. In particular, humans have each their own specific mental model [16]. Not only they use rather qualitative terms (like, e.g., "cold", "fast", "near"), but also they have each their own subjective interpretation of these terms. Additionally, this interpretation is also context-dependent: a same person may not consider "cold" in the same way in the morning and at night, in the office or outside.

In order to assess the usability of information, the system must deal with the different formalisms of data providers and especially being able to compare explicit data with implicit ones influenced by humans internal mental models. The use of ontologies decreases ambiguity in context information aggregation by allowing raw explicit data to be mapped or described using concepts. It also enables inference mechanisms on the currentness or usability of information (e.g. an outdated measure of temperature should impact a context profile built with this information) [1]. Nevertheless, the imprecise and context-dependent data gathered from human information providers (including user interests) can be best represented using fuzzy sets. The coherent representation of information provided by digital sensors as well as human information providers in ontologies remains a challenge, to which we contribute to give an answer in the next section.

3 Using linguistic values in ontological representations

3.1 Motivations

Linguistic values are imprecise notions usually used by humans to characterize something. Terms like "young", "hot" or "far" are examples of such values, corresponding to so-called linguistic variables (respectively, "age", "temperature" and "distance"). When it comes to recommender systems, they can be used to simplify the expression of user interests and to more precisely express the behaviour of the system at the boundaries of an interest. The usual way of dealing with these linguistic values is using fuzzy sets [14][24].

The interest of fuzzy logic for recommender systems has been illustrated in, e.g., [21], [10] and in [9]. In combination with description logic, fuzzy sets can be used to represent the membership of an individual to a concept. However, in recommender systems, the user is a central element, and from a user point of view, having to define such a degree of belonging may not be intuitive. For example, what means for him being "young" at 80%, or that the weather is 20% cloudy? A more suitable approach would be to first define linguistic values such as "young" by defining their associated membership functions [17], and let the user use linguistic values only.

Such an approach has the advantage of preserving the users own mental models. For example, one can define the concept "young" as someone with an age between 0 and 15, while another person can define it as being between 0 and 40. This can be made even more precise by defining a membership function, specifying, e.g., some progressive transition to get from "young" to "old". With existing recommender systems, it is often not possible to express such complex preferences as "I am looking for a restaurant with prices up to 20EUR but I could accept up to 25EUR even if I would be less satisfied". This is illustrated by Figure 1, where the *johnCheap* concept is defined as a membership function specifying that the interest for restaurants is full (=1) until a price of 20 and decreases for higher prices, until 25 where it becomes null (=0). Using membership functions thus allows defining how the interest evolves when the recommended content deviates from an ideal preference. The system would then be able to map a standard (e.g. numerical) value into a user specific fuzzy representation and from a user to another one.

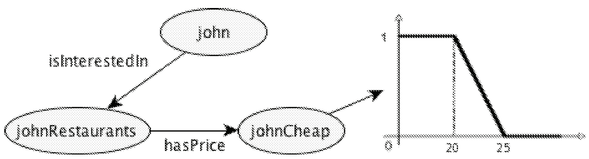

Fig. 1. Decreasing user interest represented by a fuzzy set.

3.2 Representing Linguistic Values within Ontologies

The two main research stakes are finding a way to store fuzzy information in combination with classic semantic web formats like OWL, and defining a mechanism to reason over this fuzzy Description Logic (DL). We retained two approaches. Straccia [17] proposes a new formalism different from OWL, to express fuzzy DL, together with a dedicated reasoner capable of dealing with common membership functions. This solution however lacks interoperability and usability: ontologies must be expressed using a dedicated syntax, and membership functions are described using parameters having no direct meaning for the user. The approach is slightly different in [6], as they tried to introduce fuzzy logic in such a way that they could still use a classic DL reasoner without extensive modifications. New predicates $\leq_{a\pm b}$ and $\geq_{a\pm b}$ have been added by defining new XML schema *simpleType*, and a modification of the Pellet reasoner integrating a fuzzy datatype reasoner is proposed.

The latter solution already brings wide possibilities and preserves interoperability with existing ontology languages, but the integration of fuzzy logic is limited to datatype properties in OWL. Based on this idea we propose a model, illustrated in Figure 2, to represent fuzzy sets directly into an ontology instead of using new XML datatypes. This is motivated by the need to allow personalised definition of fuzzy sets in ontologies, while preserving interoperability.

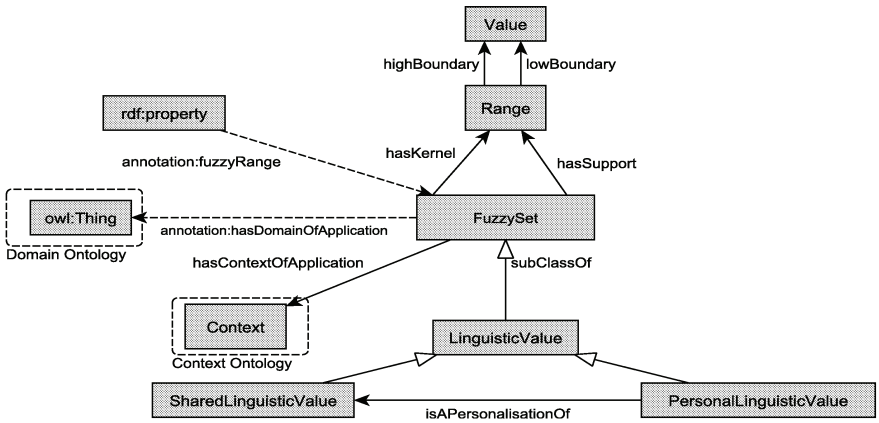

Fig. 2. The fuzzy sets model

Most commonly used membership functions (*e.g* triangular, trapezoidal, left or right shoulders) can be represented by defining only the kernel and the support of the fuzzy set. The kernel is the set of elements x where the membership function $\mu(x) = 1$; the support is the set of elements x where $\mu(x) > 0$. The *FuzzySet* concept is defined by two object properties, *hasKernel* and *hasSupport*, defining the associated membership function.

Because the meaning of a linguistic value can depend on the user context, each one can be associated to an application context by the *hasContextOfApplication* property. For instance, the meaning underneath the term "hot" depends on the season and on where the action takes place. The *Context* concept in our model represents the main class in a dedicated context ontology such as in [12], formalizing useful contextual elements.

Besides, the definition of linguistic values can be different from one user to another. The *personalLinguisticValue* concept aims at representing this possibility to have a personalised definition of a shared term, of which a common definition is given using *sharedLinguisticValue*. The property *isApersonalisationOf* allows keeping a link between this personalised value and the corresponding shared term. The shared values are meant to be pre-defined in ontologies, while the personal ones will be part of the user profile. Additionally, while the later could be defined by the user himself, it will most of the time be evaluated through an implicit profiling process. Machine learning techniques would typically be exploited in this case.

We also need to deal with the fact that the meaning of linguistic values also depends on the domain of application. The meaning of the term "tall" will be different whether it is applied to, e.g., jockeys or basket-ball players. The *hasDomainOfApplication* property is defined to solve this problem. With it we can define, e.g., a linguistic value "tall" which will be used when the subject of a property "height" is an instance of a "Jockey" class and another linguistic value "tallBasketPlayer" which will be used for instances of a "Basket-ball" class. As OWL-DL requires types separation the property *hasDomainOfApplication* is defined as an *owl:AnnotationProperty*.

After having conceptually modelled fuzzy sets and linguistic values, a way to integrate seamlessly with classic ontologies needs to be added. For example, let us assume an OWL ontology containing an *age* datatype property whose domain is a class *Person* and whose range is *xsd:Integer*. We would like now to add the possibility of using linguistic values, *e.g* "young", to describe the age of a person. A naive approach would be to modify the range of the *age* property to something like $xsd{:}Integer \sqcup LinguisticValue$. There are two majors problems with this idea. First, it implies to modify the ontology. Secondly, OWL DL imposes a separation between object properties and datatype properties. Then we cannot have a property whose range is the union of a datatype and a class. To deal with these limitations, we finally propose to use again annotations. The *owl:Annotation fuzzyRange* will allow linking an existing linguistic variable defined by a property, *e.g age*, to our *LinguisticValue* class.

To summarize, the model of Figure 2 allows the representation of most usual membership functions, the personalised definition of linguistic values, the fuzzyfication of existing ontologies without modifying them directly, and the compatibility with existing OWL DL reasoners. It does not directly allow fuzzy description logic reasoning but it is possible to develop parsers mapping fuzzy ontologies represented using this model into the syntax supported by different fuzzy DL reasoners: fuzzyDL [4], DeLorean [3] or Pellet modified reasoner [6].

3.3 Application to a context ontology

In classic ontological context representations we usually find datatype properties such as *temperature* or *distance*, qualified with numerical values. Using our model for introducing linguistic values will allow a user to express a contextual information or a context of validity of his/her interests more intuitively. In the latter case, during the recommendation process, the current context of the user is compared to the user preferences. It is at this point that the crisp numerical values from sensors can be compared to the linguistic values thanks to the membership functions. For instance, consider a temperature sensor providing a value T. The system can compare this value to linguistic values related to temperature and, by using their membership functions, it can determine to which extent the value T corresponds to each linguistic value. The results is a list of linguistic values associated to a degree of membership. For example, a temperature T of 10°C could be represented as ("cold", 0.6);("moderate",0.2);("hot";0). Figure 3 illustrates the use of our model with an example where a "temperature" context element is defined using linguistic values. The values "hot" and "cold" are specified by shared membership functions, while the user John has a personal definition for "cold".

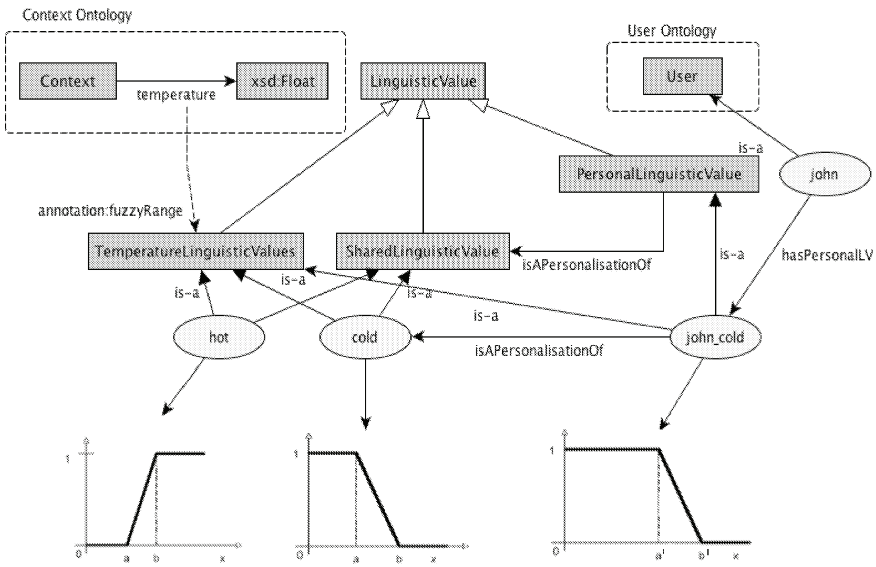

Fig. 3. The fuzzy sets model applied to a context ontology

4 Conclusion and perspectives

In this this paper, we have first discussed issues related to context-aware recommendations in mobile environments and quality of context in particular. One of these issues is the heterogeneity of data representation between humans and sensors. To start solving it, we have proposed a model allowing to introduce fuzzy sets and linguistic variables in ontologies. This model has the following characteristics: it can be used in an extension of an ontology without requiring any modifications of the latter; it allows assigning both default and specific fuzzy membership functions to a (rdf) property; it permits the mapping between crisp data and fuzzy sets in an obvious manner; and it moreover supports context and domain dependency.

Regarding the issues arising in mobile networks, we have shown this approach allows expressing user-specific interpretations of things. The model will allow us exploiting user-originated information expressed with linguistic variables. This will be particularly useful in ad-hoc networks where users exchanging information act themselves as abstract sensors regarding context data gathering. Moreover, it can be exploited to specify variable user interests following a fuzzy membership function. This allows defining the variation of user preferences and interests at their boundaries. In the same way we could specify variations of sensor inputs according to influence parameters.

Recently, Fuzzy logic has been used in [5] for situation-aware mobile recommendation of services. Situation is inferred with ontological reasoning, where a fuzzy layer allows dealing with vagueness in the inference rules antecedents. Like us, the authors have highlighted the need to offer users a more intuitive way to express interests and to deal with imprecision of context data. Their approach is however slightly different. Fuzziness is handled in rules and is related to specific properties in their ontologies, like "is-close-to", or "is-around". In our approach, we allow more flexibility by proposing a way to fuzzyfy any property of an ontology. Regarding linguistic values, [5] considers them as application-dependent. This is partially true, since they can also depend on the domain. But whatever the case, they are first of all user-dependent and might be defined differently depending on the user mental model, as we have explained.

The preliminary research reported here will serve as a modelling basis in the design of a framework for user- and context-aware information transmission in hybrid networks. By better capturing real life data, and exploiting the coupling of ontological and fuzzy reasoning to deal with context aggregation uncertainties, we aim at enhancing the quality of gathered and interpreted context, and thus the user perceived quality of recommendations. This goal could be facilitated by designing a common representation model for context data whatever its origins. We have explained that crisp values provided by sensors could be easily mapped to user-defined fuzzy sets, but another possibility is also to express any sensor input using fuzzy memberships associated to linguistic values. This has been exploited in [13] coupled with Bayesian networks in a context-aware music recommendation system. This option needs to be investigated.

Next steps in our research will be to exploit this model in previously developed user and context ontologies [12]; exploring also different crisp or fuzzy representation models for context data to ensure seamless mappings; and defining accordingly rules and appropriate extensions of a fuzzy DL reasoner. Remaining issues are also the handling of partial truth and uncertainties in context aggregation, as well as provenance and trustworthiness.

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Towards a Multilingual Semantic Folksonomy

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Abstract. The content of collaborative tagging systems (so-called folksonomies) is generated, consumed, and annotated by the end users. Users annotate and categorise their data using free-keywords, so-called tags. Consequently, several linguistic problems come to the surface in folksonomies such as; synonyms, polysemy, multilinguality, and others which produce ambiguous and inconsistent classification of data. Therefore, relevant results are not retrieved in the user's query. In this paper, we suggest a novel approach to enhance the "social vocabulary" presented in folksonomies with the "controlled vocabulary" presented in Semantic Web ontologies. Therefore, our proposed approach uses the online WordNet lexical ontology in addition to the EuroWordNet multilingual lexical resource. Our approach tries to employ the ontological relations presented in WordNet in the folksonomy, it focuses on the problems of synonyms, tag relations, and multilinguality.

Keywords: Social Web, Semantic Web, Collaborative Tagging System, Folksonomy, Ontology, WordNet, EuroWordNet.

1 Introduction

By introducing Web 2.0 (Social Web), end-users became at the heart of Web content generation and classification processes. In collaborative tagging systems (folksonomies), users generate contents and they use free-text keywords, so-called tags, to classify their contents. Therefore, users create metadata as well as data. This new approach of data categorisation and metadata creation is simple, easy, fast, low cost, and flexible compared to traditional metadata creation process by professionals and authors. Furthermore, it dynamically reflects the emergent vocabulary used among online social communities. Nevertheless, lack of semantics among data in such communities represents a real challenge regarding the information retrieval.

The ethos of Semantic Web vision is to represent the data in such a way that computers can understand. Thus, Semantic Web ontologies offer an efficient resource of structured data that can be exploited by the Social Web. Together, Social Web and Semantic Web can produce a harmonised duet.

Section 2 is devoted for the challenges of folksonomies. We demonstrate our approach in Section 3, followed by a discussion in Section 4. In Section 5, we review some related work, and conclude in Section 6.

2 Challenges of Folksonomies

By analysing the current collaborative tagging systems, we can notice that the main problems are ambiguity, inconsistency, and redundancy problems [1, 2, 3, 4]. This is normal since the collaborative tagging systems (by their nature) are shared by many users. These users came from different backgrounds, cultures, countries, domains, and tongues. The diversity of the users' behaviours would inevitably create inconsistent tags that would give ambiguous identification of the tagged objects.

The ambiguity and inconsistency of the tags in folksonomies emerge mainly because of linguistics reasons such as; word synonyms [1, 2, 3, 5, 6, 7], polysemy (homonym) [1, 2, 5, 6, 7], different lexical forms [2, 5, 6, 7], alternative spellings [2], misspelling errors [1, 2], and use of different languages [4, 8, 9]. When searching the folksonomy, these problems cause irrelevant result to be retrieved, and relevant results not to be retrieved. Our concern in this paper is the latter case.

3 Our Approach

As aforementioned, we focus in our approach on synonyms, multilinguality, and initiating relations among tags in folksonomy based on the semantic relations existing in the ontology. Since all these challenges are lexical ones, the best choice is to use the lexical ontology WordNet. WordNet is a lexical ontology which has set of synonym words, called *synset*, that defines a particular concept. It includes a lot of lexical and semantic relations between words and synsets. It is restricted to no specific domain and covers all common parts of speech; nouns, adjectives, verbs and adverbs [10].

3.1 Synonyms

Usually, when a user is tagging, (s)he is not aware of all synonyms for the tags (s)he uses. If the tagger is English, (s)he will use the word "*lift*" whilst the American one will use the word "*elevator*" to describe the lifting device used to move people from one floor to another in a building. Also, when we want to express the beauty of something, we will use words (synonyms) like "*beautiful*", "*pretty*", and maybe "*gorgeous*". Always we miss some of the synonyms. In the first example, if the tag that was used is "*lift*", the future search will retrieve nothing if we use the word "*elevator*" as a search keyword.

Our idea is to add "*system tags*" every time the user adds tags. The system tags will be added automatically by the collaborative tagging system by consulting the WordNet ontology, these tags are all the existing synonyms in WordNet for the "*user tags*". Figure 1 shows subset of the synonyms set that

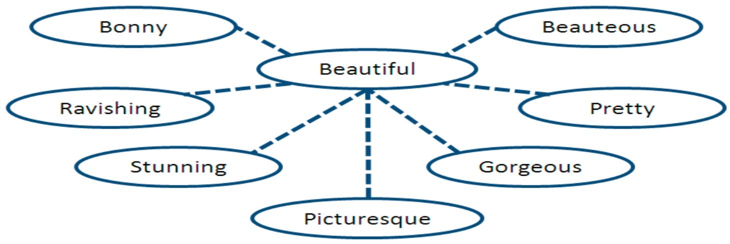

Fig. 1. Some Synonyms for The Word "*Beautiful*" Obtained from WordNet Ontology.

can be added by WordNet ontology for the tag "*beautiful*". When the user adds the tag "*beautiful*", the system will add all related synonyms from the WordNet. Future search using any of the synonyms added by the system (system tags) will be able to retrieve the tagged object. Thus, it ensures the retrieval of relevant results.

3.2 Tags Relations

Imagine if a user tagged a resource as "*poultry*". Poultry is indeed kind of meat and it is expected to be retrieved when searching using the keyword "*meat*" because it is relevant to the search keyword. Unfortunately, it will not be in the result set since this word is not in the tags set for that resource. The same problem is faced again; relevant results are not being retrieved due to lack of semantics in the folksonomy.

The WordNet ontology has such a semantic relations among words. Figure 2 shows a part of the WordNet ontology. The system will add the synonyms of the "*poultry*" (*gallinacean*, *fowl*). Also it will add the parent of that word (*meat*) and its synonym (*flesh*) as system tags. Therefore, anyone who searches using the keyword "*meat*" will retrieve the resource originally tagged with "*poultry*".

3.3 Multilinguality

So far, the tagged resource is accessible and visible only if the search keywords are English words. If a non-English speaker is searching using non-English keywords, nothing will be retrieved. If an Italian is searching using the word "*bello*" (it means: beautiful), the tagged resource in the previous example will seem as irrelevant and thus will not be retrieved. As humans, we can see clearly that it is relevant, but the machines do not.

As a solution for multilinguality problem, we will use the EuroWordNet. EuroWordNet relates and unites WordNets in different European languages (Dutch, Spanish, Italian, German, French, Czeck, and Estonian) in a single multilingual lexical resource, and it links them to the English WordNet [11].

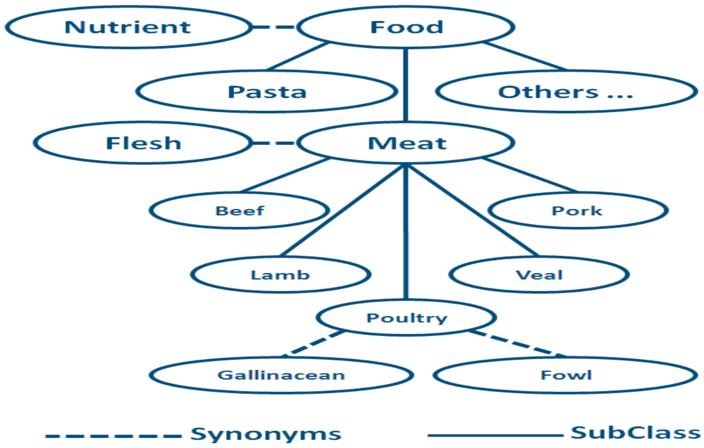

Fig. 2. Part of WordNet for The Word "*Poultry*".

We propose that EuroWordNet will find the equivalent words for the tag "*beautiful*" in the abovementioned languages using so-called Inter-Lingual-Index (ILI). These equivalent words (In addition to their synonyms and parent words as aforementioned) will be added as system tags. This guarantees that future searches by non-English speakers using their own languages will retrieve the relevant resource even if these resources were tagged originally by only English tags, and vice versa.

4 Discussion

The proposed approach requires replicating the WordNet and EuroWordNet words and storing them in the folksonomy as system tags. This redundancy of data is justified in the following paragraphs.

Alternatively, we can avoid adding system tags at *tagging time* by consulting and deducing the relations from the lexical resources at *search time*. In the case of synonyms in the previous example, when the user uses the keyword "*pretty*" in the search, the system will send it to the WordNet. The WordNet will send all the found synonyms to the folksonomy, and thus all objects that are tagged by any of these synonyms will be retrieved (See Figure 1).

This communication between the folksonomy and the ontology and the searching process inside the ontology itself is time consuming while the user is waiting for a response. We have the choice either to save time or to save space. Time is the critical factor in such a case.

Our proposal needs a software agent that is responsible of reflecting any prospective future changes in the online lexical resources on the folksonomy to keep the system tags in the folksonomy up-to-date.

5 Related Work

Many researchers have tried to address the abovementioned challenges of folksonomies using different approaches. One of these approaches was to use the power of the Semantic Web in decreasing the ambiguity an inconsistency of tags. If we have a glance at these attempts, we can see that there are still many gaps to fill.

In [8], tags are filtered and normalised, then these tags will be adhered to different domain ontologies' concepts, and only the terms that appear in the ontologies will be selected. In this method they remove some users' tags which reflect part of the users' understanding of the tagged object. Moreover, the changes in the users vocabulary will not be reflected in the semantic ontologies.

In [12], they correct the misspelled tags and group the similar tags together, and then the tags are mapped to online ontologies. This method then replaces some tags with corresponding concepts in the online ontologies. We argue that the interference in users' tags will conflict with the ethos of folksonomies (free-keywords).

In [7], they developed their own folksonomy system using domain-specific ontology and WordNet ontology. They detect the domain of the most popular tags, and then they manually build an ontology for that domain. The problem in this method is the necessity of building the domains ontologies, even worse; the domain ontology should be built manually.

In [13], they used the WordNet concepts' relations to show the user an additional panel on his browser's interface. This extra visualisation displays related tags organised according to a semantic criterion to facilitate navigation and searching in the folksonomy. It is only visualisation nothing more and some tags were not recognised in the lexicon.

In [14], they map the unstructured tags to more structured domain ontologies. These ontologies are used for refining the queries to combine results of different tag-based systems. This method uses an ontology-based navigation interface allowing the user to retrieve more related results through graphical navigation of the ontology concepts. This method can not deal with unmatched tags; which are the tags that do not exist in the domain ontologies.

In [2], they use WordNet and Wikipedia to substitute semantic assertions for the current tags. These assertions are not simple strings to describe a particular resource; each semantic assertion describes a specific property of a resource. Therefore, the possibility of tagging using free words is absent which contradicts the ethos of folksonomy.

In [15], they apply both syntactic and semantic techniques for connecting tag to ontologies in order to get more semantics about the tag and provide tag suggestions for the users. This method, in addition to offering suggestions to the users, asks the users to give feedback about these suggestions. Hence, we argue that it puts more effort on the users' side to improve the quality of the tags by changing the conventional way by which the users used to interact with the folksonomy.

6 Conclusion

Folksonomies lack semantics among users' tags which causes relevant results not to be retrieved. Semantic Web ontologies are considered a rich source for semantic relations that, if exploited properly, will improve the searching process in folksonomies. Our approach focused on addressing the problems of synonyms, semantic relations among tags, and multilinguality. It is based on the idea of adding *system tags* as complements to the *user tags* for a wider coverage of potential future search keywords, therefore, more relevant results will be retrieved.

7 Future Work

In the future, this proposal will be implemented therefore more empirical results will follow.

EuroWordNet is limited to only some European languages. Our approach is extendable to other languages by using intermediate online dictionaries. These dictionaries might be used to translate from one WordNet to another for languages that are not included in EuroWordNet (e.g. from English WordNet to Arabic WordNet).

A unifying architecture for collaborative tagging systems is under construction. This architecture includes clustering techniques to address the problem of shorthands usage in tagging. Such tags are written using special words that do not belong to any language. Therefore, the best choice is to consult the social networks to predict their meanings.

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Applying a Multi-gated News Model to a Social Web

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Abstract: Traditional Newspapers have been struggling to find a new business model to economically survive in this new wave of digital social revolution. This study uses ontology of a multi-gated model to suggest that program designers use different kinds of most popular news cues to satisfy diverse citizens' needs. Different concepts of citizens are discussed theoretically in exploring how a social semantic perspective based on various meanings of news cues might help news users to participate or disseminate news stories by social media.

Key Words: news cues, most popular news, gatekeeping, news attention

1 Introduction

The trend of online news use is changing fast. According to the Pew Internet and American Life Project, people's relationship to news is now becoming portable, personalized, and participatory [1]. In terms of being portable, 33% of cell phone owners now access news on their cell phones. From the personalized perspective, 28% of Internet users have customized their home page to include news from sources and on topics that particularly interest them. As to the concept of a participatory Web: 37% of Internet users have contributed to the creation of news, commented about it, or disseminated it via postings on social media sites like Facebook or Twitter. More than 8 in 10 online news consumers get or share links in e-mails. Therefore, online users consume news aiming not only to convenient news use but also social participation.

Nowadays, mainstream news media or portal news sites offer different most popular news lists to users for news selection. However, we rarely see mainstream news sites offer these different kinds of most popular news lists as applications to social or mobile media (See Table 1). It seems that managers of a news site don't consider their most popular news cues as an ideal tool that can be applied to a social and participatory Web. News use is becoming a shared social experience as people swap links in e-mails, post news on their social networking site feeds, exchange news stories in their Tweets, or discuss threads for hot topics or events as the Pew Internet and American Life Project suggests. This paper theoretically discusses why designing different kinds of most popular news lists as applications for social media has important potential for online users' various sharing purposes.

Table 1. An example of a list of most popular news, collected by Yahoo! News. (A similar list rarely presented as a live feed in social media such as Facebook.)

2 News Attention and Multi-gated News

Exploring how different designs of news cues may affect online news consumption, scholars have proved online news users use different news cues to select news. Different designs of media salience cues [2,3,4,5,6,7,8] influence the roles of media as gatekeepers and agenda-setters. Study also shows that different kinds of most popular news, selected by people, contain different social meanings [9]. Applying a multi-gated model, the author explores meanings of various gated news by defining citizens who have different patterns of news selection. This research provides a theoretical argument to discuss the possibility that different kinds of most popular news cues are potentially personal or social tools for users' news attention[10].

Scholars commonly use technology, market, and democratic theories to explain the process of news gatekeeping for new media. Bennett uses a multi-gated model to demonstrate how the economy, journalism, technology, politics, and publics shape news content[11]. Bennett's model offers four dimensions—reporter-driven, organization-driven, market-driven, and technology-driven—to define who uses news, what is news, and what roles news media play. In this study, the author adjusts Bennett's model and further develops four types of gated-news by identifying the concepts of public, journalistic roles, gatekeeping norms, and online users' decision basis for news selection (See Fig. 1).

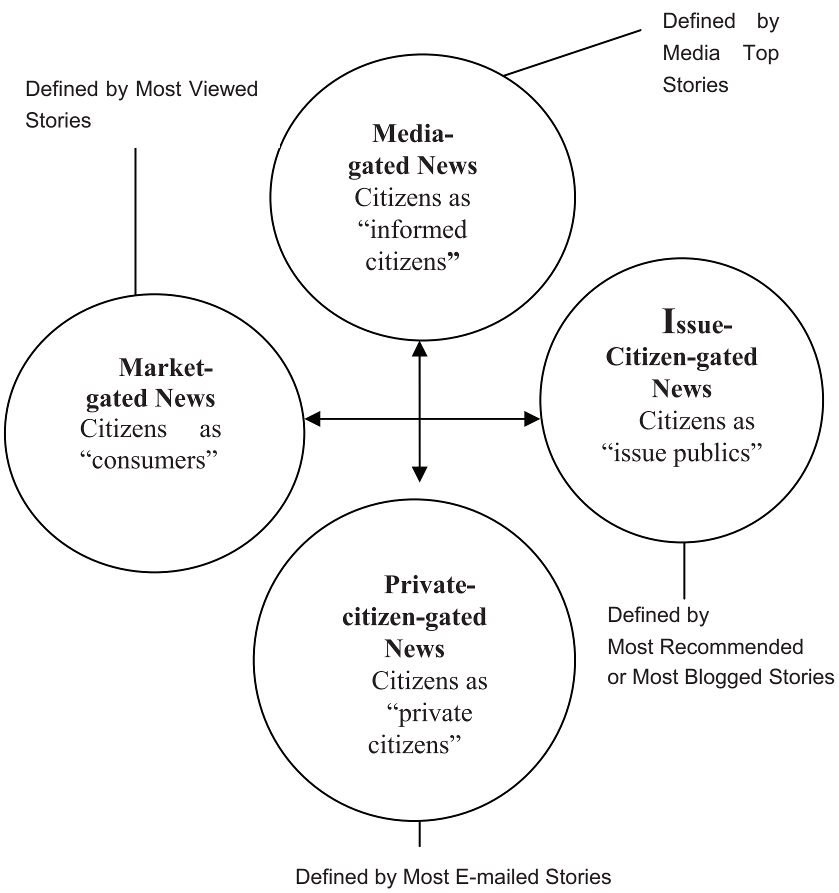

Fig.1. A Multi-gated model explains how four kinds of gated news cues compete for online users' news attention.

(Note: Two black arrows represent the competition of four kinds of gated news cues on people's news attention.)

In Bennett's model, from a reporter/organization-driven dimension, the concept of citizens is engaged citizens and social monitors who are concerned about public interest. In addition, he describes the journalistic role of this dimension as a watchdog and record keeper and news is defined by journalists, officials, and established interests. People usually follow top news selected by editors are regarded as informed citizens.

From the market-driven dimension, the concept of citizens is entertainment audiences that are concerned about consumer content. From this perspective, Bennett considers the journalistic role as a content provider, and the decision basis of news media is profits and the audience's demographics. Because the norm of news definition is “plausibility”—whether it makes a good story if plausible, its information gathering process turns news into infotainment as the media focus on market formulas. According to the market-driven dimension, most viewed stories can be treated as market-gated news.

From the technology-driven dimension, Bennett describes the journalistic role as a transmitter, sending news content to the audience. The concept of citizens is interactive citizens who interact with news content by sending information to others. Two types of interactive citizens are further identified in this study—private citizens (online users who e-mail stories to others) or active citizens (online users who recommend stories or write blogs and add a story link to a blog). E-mailing news to people they know, private citizens pay attention to information or issues related to their private life or individual rights. In contrast, online users as active citizens pay attention to public affairs and interact with others by recommending stories or writing blogs. Therefore, private-citizen-gated (most e-mailed) news should be related to individual issues or matters about private life; in contrast, news characteristics of active-citizens who recommend news or blog news and put news links to their blogs should pay attention to public affairs or public issues.

3 News Characteristics and Multi-gated News Cues

The four kinds of online users in this model are defined as “informed citizens,” “consumers,” “interactive private citizens” or “the interactive issue public.” Study shows that these four kinds of gated news have distinctive news characteristics [9]. Therefore, developing the ontology of this multi-gated model helps explain how different kinds of most popular news attract citizens’ news attention. For those who read media-gated news (media top stories), the public acts as “informed citizens” and is more likely to follow hard news. The rationale is that the reporter and news organizational dimensions reflect how news media fulfill their social responsibilities by focusing on presenting news about what people need to know such as hard news and issue stories. For those who read market-gated news (most viewed news), the public acts as “consumers” and is more likely to choose soft news or sensational news. If news media adopt a business model, media will offer them what people want to know such as sensational news and soft news. From the technology-gated dimension (most e-mailed/recommended news), news media create interactive citizens that choose to interact or share news content with other and are more likely to choose hard news, issue stories or soft news that is useful to individual citizens.

According to Burnett’s model and the concepts of characteristics of four kinds of gated news, characteristics become good factors in analyzing the content of most popular news because news characteristics reflect online users’ uses and gratifications. In addition, news cues of media-gated news, market-gated news, and private-citizen-gated news are significant group factors in testing and explaining online users’ news attention [12] (See Table 2). From Figure 1 and Table 2, we can infer possible interactions between various concepts of citizens based on news cues and that suggests a semantic Web design, if reflecting objects’ relations among specific actors and agents, might possibly push group or public dynamics.

Table 2. Spearman Partial Correlations between News Cues and News Popularity[1]

Rank Scores / Aggregated News Cues		**Yahoo! News**		**Washingtonpost.com**	
		Most Viewed Stories	Most E-mailed Stories	Most Viewed Stories	Most E-mailed Stories
Editors' News Cues	Zero Order	.32**	.74**	.51**	.50**
Most Viewed News Cues	Zero Order				.56**
	4th Order [a]				.52**
	5th Order [b]				.35**
Most E-mailed News Cues	Zero Order	.30**			
	4th Order[a]	.32**			
	5th Order [b]	.24**			

[a] Partial rank order correlations were controlled by news characteristic.
[b] Partial rank order correlations were controlled by news characteristic and aggregated editors' news cues.
*p<.05, **p<.01 (two-tailed tests). An empty cell means no tests conducted for it.

4 Applying Gated News Cues as Attention-setting Factors for a Social and Sharing Web

Based on the results discussed above, this paper theoretically draws two trends of news consumption (See Figure 2): First, most popular news characteristics and news cues imply different purposes for users' news selection. Second, news editors can apply different news cues to social media to broaden news use as social sharing tools to serve the various concepts for citizens. A potential development of a social semantic Web might answer the question—what are social consequences of interactions invoked by the connection of various concepts of citizens together? Related tests are still in progress by connecting online public forums and issues with various kinds of citizens, defined by news cues that are set and presented by social media.

5 Discussion

1 News content and most popular news rankings were downloaded from news sites four times a day for the two weeks of November 15 through November 28, 2006. The download times were 8 a.m., 12 p.m., 6 p.m., and 10 p.m. that represent morning news, news at noon, evening news and nightly news. This download plan is designed to reach online users with various surfing schedules. There are 3,341 stories in total analyzed in this study. Please see the methodology in detail in *Exploring the Potential of Most Popular News Cues as a Web 3.0 Interactive Tool and Its Public Nature* [12].

It is important to discuss a social semantic Web from an interdisciplinary perspective because semantics of Web influences how citizens see themselves as consumers, issue publics, or private citizens. From a communicative perspective, program designers become more important because they influence how citizens select news based on news cues they design for Web sites. This paper suggests more scholarly cooperation in the fields of computer science and social science to explore how a semantic Web, designed as most popular news cues, has important implications for public and social consequences.

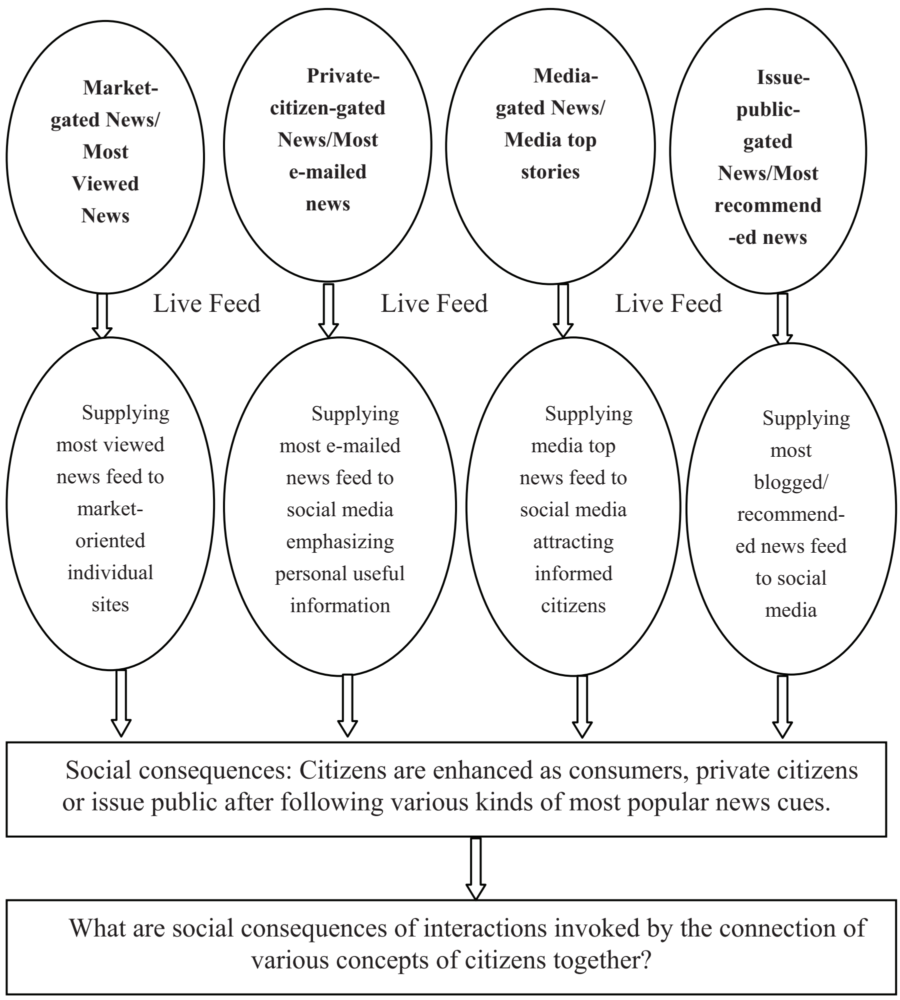

Fig. 2. Four kinds of gated news cues applied to attract social media users' attention based on what kinds of citizens they are.

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