WP7-D71

User Model Definition (V2)

Project full title:	Knowledge Driven Data Exploitation
Project acronym:	K-Drive
Grant agreement no.:	286348
Project instrument:	EU FP7/Maria-Curie IAPP/PEOPLE WP 2011
Document type:	D (deliverable)
Nature of document:	R (report)
Dissemination level:	PU (public)
Document number:	UNIABDN, ISOCO, ESI/WP7-D71/D/PU/b1
Responsible editors:	Honghan Wu, Ronald Denaux, Panos Alexopoulos, Boris Villazon-Terrazas, and Jhonatan Garcia
Reviewers:	TBD
Contributing participants:	UNIABDN, ISOCO
Contributing workpackages:	WP7
Contractual date of deliverable:	30 June 2014
Actual submission date:	30 June 2014 (v1); 20 July 2015 (v2)

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Keyword List
User Modelling, Literature Review, Survey

Project funded by the European Commission within the 7th Framework Programme/Maria Curie Industry-Academia Partnerships and Pathways schema/PEOPLE Work Programme 2011.

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Contents

1 Introduction

Workpackage 7 of K-Drive aims to extends the previous work on Intelligent User Interfaces (WP4) by investigating how user modelling and adaptation techniques can be used to further help users to exploit public semantic datasets.

In WP4 of K-Drive, we developed a user interface that allows users to define their requirements for datasets and to view summarisations of various datasets. The system, described in D4.3, helps users by hiding some of the complexity of accessing datasets directly and composing various types of queries to find metrics for specific users' dataset requirements. As discussed in D4.3, the system is best suited for users with some basic knowledge of the semantic technologies underlying the semantic web as users (i) need to know enough about their requirements, (ii) need to know some of the terminology related to RDF data models, and (iii) they may need to enter URIs when defining some of their requirements.

While the system already improves the analysis and thus the potential exploitation of public semantic datasets, the system's focus on one type of user limits its potential for fostering dataset exploitation. On the one hand, the system cannot currently be used by end-users without any knowledge of semantic web technologies as they would need to receive training beforehand. On the other hand, users who are experts in semantic web technologies, may find the system useful but too limited for their needs. Hence there is a need for the system to be able to adapt to the various types of users who may be interested in reusing public semantic datasets, but who have different requirements for the user interface to help them summarise datasets.

In order for the system to be able to adapt to the various types of users, we first need to define what aspects of users the system will need to model in order to subsequently adapt its interface. This is the main aim of this deliverable. Since we have not considered user modelling and adaptation in the context of K-Drive before, we will first review the current state of this research area in the context of LOD in order to (i) put our work into context and (ii) find out whether there are existing approaches that we can extend and improve.

In the remainder of this Deliverable, in Section 1 we will first present a survey of how the research areas of LOD and user modelling and adaptation have been combined in recent years. We will see two main approaches: (i) vocabularies are being developed to represent and exchange user profile information and (ii) user models are being enriched by using public semantic datasets. Next in Section 2, we will present an analysis of how User Models can be used by the dataset summarization system in order to be able to support a wider user base. In doing so, we will define requirements for the User Model and we will also highlight vocabularies and LOD enrichment outputs from the survey in Section 1 which we can reuse.

2 Survey

This systematic review was conducted by two reviewers from the same institution following the systematic review procedures described in Kitchenham (2004). According to Kitchenham (2004) a systematic review can be conducted for several reasons like for example (a) the summarisation and comparsion, in terms of advantages and disadvantages, of several approaches in a field; (b) the identification of open problems; (c) the contribution of a joint conceptualization comprising the various approaches developed in the field; or (d) the synthesis of a new idea to cover the emphasized problems. This survey tackles the problems (a) and (b), in that, it summarises and compares (1) various user modelling vocabularies as well as (2) approaches for enriching users profiles by means of LD datasets.

2.1 Related Surveys

In order to justify the need of conducting a systematic review, we first conducted a search for related surveys and literature reviews. There are some surveys related to (i) user profile modeling for personalized service delivery systems McTear (1993); and (ii) user modelling interoperability Carmagnola et al. (2011). Therefore, we think this survey is going to be the starting point for the community, and it can be extended in the future with new approaches and models.

2.2 Eligibility criteria

As a result of several discussions between the two partners, Aberdeen and iSOCO, a list of eligibility criteria was obtained as follows:

- Inclusion criteria
  - Studies published in English till 2013.
  - Studies focused on developing models for user profiles.
  - Studies focused on enriching user profile information by means of Linked Datasets.
- Exclusion criteria
  - Studies that were not peer-reviewed or published.
  - Studies that were published as a poster abstract.

2.3 Comparison Framework

In this section we set up a framework for comparing the approaches related to user modelling and Linked Data. The survey is grouped by two main trends (1) models for represeting user profile information, and (2) approaches for enriching user profile information by means of Linked Data datasets.

2.4 Building vocabs for representing user profile information

- Tsatsou et al. Tsatsou and Mezaris (2014) presents an ontology for representing user-pertinent information in the networked media domain and to enable personalization and contextualization. According to the authors there is lack of an expressive ontology that adequately describes the broad networked media domain from the users' perspective but at the same time is not too abstract or too specific, in order to scale well and maintain the decidability of reasoning algorithm. LUMO comes to overcome this lack of ontology. The authors developed this ontology by re-using a set of well known vocabularies. Some of the features are:
  - OWL 2 RL
  - components (1) ontology, (2) modelling mappings,
  - development methodology : methontology
  - domain: media
  - influences from DBPedia ontology, NERD ontology, IPTC newscodes, General User Model Ontology mappings to DBPedia ontology, schema.org, NERD ontology, IPTC newscodes, General User Model Ontology

- available at http://data.linkedtv.eu/ontologies/lumo/

- Heckmann et al. Heckmann et al. (2005) presents a general user model ontology, GUMO for the uniform interpretation of distributed user models in intelligent semantic web enriched environments. This is a first user model ontology and it is implemented in OWL. The ontology has influences from UserML[1] (user model markup language), SUMO[2], and UbisWorld[3]. Its main conceptual idea is *SituationalStatements*, and it basically consists of the division of the user model dimensions into 3 parts: auxiliary, predicate and range. The model is available at http://www.gumo.org, first version available at http://www.daml.org/ontologies/444. Moreover, it provides a user model service on top.

- Abel et al. Abel et al. (2012) presents how LOD cloud can be leveraged as additional knowledge source in user modelling processes that exploit user data from the Social Web. The authors introduce a user modelling framework that utilizes semantic background knowledge from LOD and evaluate it in the area of point of interest (POI) recommendations. The authors infer preferences in POIs based on the users behaviour observed on Twitter and Flickr, combined with evidence from the Web of Data. Finally, the authors compare strategies that aggregate knowledge from two LOD sources: GeoNames and DBPedia. They show that the user modelling quality improves when LOD-based background information is included in the process.

- In Ye et al. (2011) authors claim that user modeling in a multi-application environment is increasingly required to provide a more complete user model view and more value-added user information to all relevant applications. Linked data-driven user modelling approach is proposed to create links among the user model fragments of the same user who registers in different applications, and build from here a global user model. This model is used to describe common properties and domain-specific features. The model is not available.

2.5 Enriching User profile information by means of LOD

Due to recent development in semantic web and the explosive growth in Linked Open data, researchers have been making use of LOD for dealing with the cold start problem in recommender systems. For example, in Heitmann and Hayes (2010), Heitmann et al. utilised Linked Data to mitigate the new-user, new-item and sparsity problems of collaborative recommender systems. The conclusion was that the data from a closed collaborative music recommender system can be significantly improved by Linked Data in terms of precision and recall. Di Noia et al. Di Noia et al. (2012) implemented a content-based recommendation system that leveraged the data available within Linked Open Data datasets (in particular DBpedia, Freebase and LinkedMDB) in order to recommend movies to the end users. Authors also reported the improvements in accuracy with precision and recall metrics. Peska et al. Peska and Vojtas (2013) selected the domain of secondhand bookshops, where recommending is extraordinary difficult because of high ratio of objects/users, lack of significant attributes and small number of the same items in stock. Linked Open Data is utilised for dealing with such difficulties. Particularly, they queried Czech language mutation of DBPedia in order to receive additional attributes of objects (books) to reveal nontrivial connections between them. The authors reported that such approach can significantly improve its results in terms of object similarity computation and top-k objects recommendation. Ostuni

[1] http://link.springer.com/chapter/10.1007%2F3-540-44963-9_55
[2] http://www.ontologyportal.org/
[3] http://www.ubisworld.org/

et al. Ostuni et al. (2013) proposed SPrank, a novel hybrid recommendation algorithm to compute top-N item recommendations from implicit feedback exploiting the information available in the so called Web of Data. Comparisons show that their algorithm outperforms the state of the art in two different domains.

There is a line of work where LOD is not directly used but similar the idea of linking distributed semantics or information sources are applied in enriching user profiles. In Abel et al. (2011), Abel et al. investigated semantic user modelling based on Twitter posts. The authors introduced and analyze methods for linking Twitter posts with related news articles in order to contextualize Twitter activities. Although the authors did not use linked data directly, their approach exploits the semantics extracted from both tweets and related news articles to represent individual Twitter activities in a semantically meaningful way. In this sense, their work is very relevant by connecting semantics from different sources for user modelling tasks. Similarly, Orlandi (2012) proposed the creation of accurate user profiles of interest across heterogeneous websites via semantic technologies for interlinking social websites and provenance management on the Web of Data to retrieve accurate information about data producers.

In another domain of Customer Relationship Management, Basaille-Gahitte et al. Basaille-Gahitte et al. (2013) proposed a community detection approach that identifies clusters of customers of a company using their explicit and implicit behaviour. This suggests that linked semantics hidden in various resources might also be helpful in CRM use cases.

2.6 Discussions and conclusions

The conclusion from this survey is two fold. In the first aspect, semantic web techniques are used in formalisation of user profiles. This enables various semantic techniques can be used not only in the data modelling task but also the system itself will benefit from the explicit semantics. In the second aspect, distributed information sources can be utilised to mitigate the new-user, new-item and sparsity problems of collaborative recommender systems.

3 User Modelling definition within K-Drive

In deliverables D1.1 and D1.2 we defined the high level requirements of a semantic dataset summarization system that should enable its intended users to answer the following question: *"Given an application scenario where semantic data is required, how suitable is a given existing dataset for the purposes of this scenario?"*. In deliverables D4.1, D4.2 and D4.3 that followed, we realized these requirements into a concrete design and implementation of a semantic data summarization system, both at system and user interface (UI) level. In this deliverable, we focus on how the data summarization system can be personalized, i.e., how it can be adapted to the particular preferences, goals and characteristics of each user. The need for personalization is related to a basic functionalities of the system, namely the recommendation of summarization tasks.

Summary recommendation involves suggesting to a given user summarization tasks that may be useful for his/her task. It is reminded that a summarization task is practically an operation on the data that, given specified parameters, produces a particular summary that illustrates some key aspect of the dataset (e.g., the coverage of a domain). Our summarization system enables a user to define his/her own custom summarization task, based on his/her needs; nevertheless a proactive recommendation to the user of such tasks by the system can be useful in the following cases:

1. When the user's intended summarization task has already been defined and applied by other users. In such a case, a recommendation of an existing task will accelerate the whole process and will

save the user time and effort.

2. When the user does not know, maybe from lack of expertise or experience, the complete range of dataset aspects that he/she needs to assess for a given task/goal. In such a case, a recommendation of summarization tasks that have been defined by similar users and for similar goals can bootstrap the whole process for the given user.

In the following sections we provide details on the user-related knowledge the system needs to have/obtain in order to facilitate this kind of recommendation.

3.1 A Static User Model

In order to be able to recommend summarization tasks to users, the system needs primarily two things:

- Knowledge about what summarization tasks a particular user prefers for a particular task/goal, so that it can recommend these to similar users.
- Some user similarity metric so that it can determine which users are similar to a given user.

For the first, we model the set of user summarization preferences as a function $Pref : U \times G \times ST \rightarrow [0,1]$, where U is the set of all users, G is the set of all possible goals and ST is the set of all possible summarization tasks that are supported by the platform. If $u \in U$, $g \in G$ and $st \in ST$ then $Pref(u,g,st)$ is the degree to which the summarization task st is considered important by user u for the goal g. Examples of goals include:

- Scientific experimentation.
- Applying analytics in order to gain insights and useful information about a particular domain or business/social problem.
- Making data available to end-users or other applications via APIs and User Interfaces.
- Using them as background domain knowledge for some knowledge-intensive task (e.g., semantic annotation, recommendation etc.)

Moreover, examples of dataset aspects for which summarization tasks have been defined include:

- **Completeness/Coverage:** The extent to which the dataset contains information about a particular domain and/or entities.
- **Conciseness:** The extent to which the dataset does not contain redundant entities.
- **Accuracy:** The extent to which data is correct, that is, the degree to which it correctly represents the real world facts and is also free of error.
- **Objectivity:** The degree to which the interpretation and usage of data is unbiased, unprejudiced and impartial.
- **Consistency:** That a knowledge base is free of (logical/formal) contradictions with respect to particular knowledge representation and inference mechanisms.
- **Reputation:** The level of reputation the dataset enjoys among its users.

- **Licensing:** The kind of license required for the usage of the dataset
- **Understandability:** The ease with which data can be comprehended, without ambiguity, and used by a human consumer.
- **Representation:** The alternative representations of a dataset.
- **Accessibility:** The available access methods for a dataset.
- *Availability:* The extent to which information is present, obtainable and ready for use.
- **Security:** The degree to which information is passed securely from users to the information source and back.
- **Volatility:** The rate at which the contents of the dataset change.
- **Timeliness:** The extent to which the dataset contains no outdated data.

The above preference function can be automatically derived from the users's history of interacting with the system to define and generate dataset summaries. As far as user similarity is concerned, in our application domain this is determined primarily by the roles the users have within their organizations and which are related to data (re-)use. Examples of such roles include:

- Scientific Researcher in Computer Science
- Scientific Researcher in other disciplines like Biology, Social Sciences, etc.
- Software Engineer/Application Developer
- Data/Information/Knowledge Architect
- Business Analyst

The intuition here is that users with similar roles will most probably prefer/utilize similar summarization tasks for similar goals. Thus, for example, if a new application developer wants to reuse data for a particular goal, it will be more appropriate to recommend him/her summarization tasks that other application developers have used for the same goal.

A second user similarity dimension can be the users' skills with respect to particular data technologies; the intuition here is that users who lack a particular skill (e.g., knowledge of RDF) may not be able to use/understand a summarization task that is primarily used by users with that skill. Both roles and skills of a given user can be obtained by means of an appropriate questionnaire, prior to the usage of the system.

4 Subjective Description Logic based User Modelling

In this section we describe our second version of user model in K-Drive, which is motivated by the lessons learnt from adopting the user model described in section 3. The original model is a static model [4] in terms of user types. Such model works very well when users can be classified into predefined categories. For example, the model can produce very good recommendations when the user is either a

[4] https://en.wikipedia.org/wiki/User_modeling

Table 1: Scenario knowledge base

$t_1 : CSResearcher \sqsubseteq ScientificResearcher$	$t_2 : BioResearcher \sqsubseteq ScientificResearcher$
$t_3 : SocialResearcher \sqsubseteq ScientificResearcher$	$t_4 : SoftwareEngineer \sqsubseteq ApplicationDeveloper$
$t_5 : DataArchitect \sqsubseteq SystemArchitect$	$t_6 : KnowledgeArchitect \sqsubseteq SystemArchitect$

$a_1 : CSResearcher(user1) : (1, 0, 0)$
$a_2 : SoftwareEngineer(user2) : (1, 0, 0)$
$a_3 : CSResearcher(user3) : (0.4, 0, 0.6)$
$a_4 : SocialResearcher(user3) : (0.7, 0.1, 0.2)$
$a_5 : ApplicationDeveloper(user3) : (0.9, 0.05, 0.05)$

software engineer or a *business analyst*. However, it is not able to give reasonable recommendations to those *middleman* users, who take multiple roles (user types) in particular scenarios. For example, when a research fellow is also doing a software engineer's job in one particular project, which is quite often in reality, the static user model is hardly able to model the user precisely. Therefore, it might result with ineffective recommendations.

To deal with the limitation of static user models, we propose a novel user model approach, which can manage the uncertainty in user type classifications and also is able to make the best use of existing static user model at the same time. Specifically, we apply our subjective DL-Lite work Garcia et al. (2015), which is designed for capturing data uncertainty, in K-Drive user models as a combination with the original static data modelling approach.

In section 4.1, we introduce the definition of Subjective ABox that is the key foundation for modelling the uncertainty. Then, in section 4.2, we elaborate the usage of Subjective DL in the user model scenario with specific examples.

4.1 Subjective ABoxes

A subjective DL-Lite$_{core}$ ABox $\mathcal{SA}$ is an extension of a DL-Lite$_{core}$ ABox $\mathcal{A}$ in which every assertion in $\mathcal{A}$ is extended with an opinion. An opinion **w** over a statement x is a triple of positive numbers (b, d, u) such that $b + d + u = 1$; and in which b represents the degree of belief assigned to the truth of x, d represents the degree assigned to the falsehood of x, and u measures the degree of uncertainty associated with x. If, during the execution of any reasoning task, an opinion **w** is produced such that $b + d + u >$ 1, we say that **w** is invalid. We denote with b(**w**), d(**w**), and u(**w**) the degrees of belief, disbelief and uncertainty associated with an opinion **w**, respectively, and with $\mathcal{W}$ the set of all possible opinions.

Definition 1 *Let $w_1 = (b_1, d_1, u_1)$ and $w_2 = (b_2, d_2, u_2)$ be two opinions about the same assertion α. We call w_1 a specialisation of w_2 ($w_1 \preceq w_2$) iff $b_2 \leq b_1$ and $d_2 \leq d_1$ (implies $u_1 \leq u_2$). Similarly, we call w_1 a generalisation of w_2 ($w_2 \preceq w_1$) iff $b_1 \leq b2$ and $d1 \leq d_2$ (implies $u_2 \leq u_1$).*

4.2 User Modelling Scenario

To use subjective Description Logic for modelling users, the first thing we will need is a T-Box that describes the concepts and their relations. In table 1 the upper one shows a sample T-Box based on the user types listed in section 3. $CSResearcher$ is a concept name that denotes Computer Science Researcher and similarly $ScientificResearcher$ represents Scientific Researcher. The axiom t_1 specifies that the two concepts have a subset relation, which means that every Computer Science Researcher is also a Scientific Researcher. Other axioms in this table specify the relations between other concepts in the domain respectively.

Once we have a T-Box, we can use the concepts, i.e., user types in this scenario, to describe individual users. As shown in the lower table in table 1, such description is called A-Box. For example, $user1$ is a computer scientist and she is asserted as the type of $CSResearcher$ in the A-Box. It might be noted that there is a triple of decimals $(1.0, 0, 0)$ attached to the assertion. As defined in section 4.1, 1.0 in a_1

means that we are 100% sure that $user1$ is an instance of $CSResearcher$, the second 0 means that we have no disbelief in the assertion and the last 0 means that there is no uncertainty at all. Similarly, a_2 means that it is very certain that $user2$ is a software engineer.

$user3$'s assertions are a bit different in the data. a_3 denotes that the user might be a computer science researcher but with 60% uncertainty, while a_4 says that she might be more likely to be a social science researcher. However, the most certain assertion we have for the user is a_5, which says that she is an application developer.

Obviously, with subjective DL, we are enabled to classify users in a more flexible way so that we can deal with the *middleman* challenge mentioned earlier in section 4. Once we can describe users in this way, the system will be able to generate queries for these users to better fill their requirements. In later tasks of work package 6, we will study the user query generation based on the user model described in this deliverable.

5 Conclusions

In this deliverable, we first dig into the user modelling approaches which make use of either semantic web techniques in modelling methodology or various distributed linked datasets to deal with the cold start problem in most recommender systems. Following the conclusion of the survey, we discuss the user modelling problem in our dataset summarisation system. We first defined what aspects of users the system will need to model in order to subsequently adapt its interface. After getting a clear definition of the requirements, we identified existing approaches that we can extend and proposed directions what are needed and what are possible to be improved in our scenario. Specifically, we propose a subjective Description Logic based approach to achieving a flexible user model.

Acknowledgement

This research has been funded by the European Commission within the 7th Framework Programme/Marie Curie Industry-Academia Partnerships and Pathways schema/PEOPLE Work Programme 2011 project K-Drive number 286348 (cf. `http://www.kdrive-project.eu`).

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