Agent-Based Customer Profile Learning in 3G Recommender Systems: Ontology-Driven Multi-source Cross-Domain Case

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Abstract. Advanced recommender systems of the third generation (3G) emphasize employment of semantically clear models of customer cross-domain profile learned using all available data sources. The paper focuses on conceptual level of ontology-based formal model of the customer profile built in actionable form. Learning of cross-domain customer profile as well as its use in recommendation scenario requires solving a number of novel problems, e.g. information fusion and data source privacy preservation, among others. The paper proposes an ontology-driven personalized customer profile model and outlines an agent-based architecture supporting implementation of interaction-intensive agent collaboration in two variants of target decision making procedure that are content-based and collaborative filtering both exploiting semantic similarity measures.

Keywords: Recommending systems · Ontology-based customer profile · Multiple data sources · Learning of customer profile · Agent-based architecture · Semantic similarity measure

1 Introduction

Advanced Recommendation Systems (RS) qualified as RS of the third generation (3G) emphasize employment of semantically clear model of customer cross-domain profile learned using all available data sources where the customer's "footprints" can provide, for learner, with useful information about customer's interest and preferences. Focus on semantic aspects of customer profile stimulates, in turn, wide spread of ontology-based meta-modeling of data sources. It is worth to note that well known fact that customers prefer to trust much more to the recommendations of their "friends" than to anonymous sources like routine advertisements is an additional argument in favor of importance of semantics in customer profiling. Indeed, the core of the customers' trust to the "friends" is their *semantic similarity*. As a result, e.g., collaborative filtering (CF) as applied to the "friend" community leads to good results due to implicit meeting the members of this community to the semantic similarity requirement.

Recent understanding of the topmost importance of the semantic basis of customers' motivations determining his/her preferences in buying of those or

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these product items results in noticeable shift of the RS-related research to the causal analysis of the customer interests and preferences, in particular, to active research on ontology-based model of particular customer interests and model of customer profile as a whole. The core of this shift is focus on well semantically-grounded personalized customer interests. Let us mote that similarity measures constituting the basis of any former versions of CF are understood as purely statistical properties. Statistical similarity measures are independent of the causes motivating the customer's selections. In contrast, 3G RS similarity measures should, first of all, to explain semantically why two customers are similar or dissimilar, although they may select the same product item. E.g. one customer can select a movie due to its favor director, whereas another one may to do the same choice due to the movie genre and/or leading actor team. Former CF ignores such facts. Therefore, customer interests presented as whole customer profile have to be clearly semantically interpretable. Let us note that such profiles should be learnt from all available data sources.

Accordingly, several novel problems appear in modeling of 3G RS. These problems formulated below as the questions are the followings:

- What can be an appropriate customer interest formal model covering its multiple interests in several domains?
- How this model interacts with the multiple domain ontologies peculiar to the applications having multiple learning data sources?
- How customer interest formal model interacts with reasoning on recommendation-related decisions?
- How semantic similarity measures of a pair of customers can look like and how these measures interact with the formal model of customer profile?

Many other novel questions exist too, but they cannot be answered in a single paper. This paper focuses on conceptual aspects of formal modeling of RS components associated with the aforementioned questions while emphasizing important role of customer profile formal model as a core of the whole 3G RS model. Another paper topic is about the novel roles of agents supporting interactions of RS components in the customer profile learning and decision making use cases.

Taking the agent mining approach [4], this work combines agent technology with ontology, customer profiling and recommender systems. To make the paper ideas and contribution more understandable, it starts with presenting of a case study data set comprising several data sets of cross-domain nature (Sect. 2). Afterwards, in Sect. 3, the proposed formal model of the customer profile satisfying the requirements to its semantically clear interpretation is described. This section sketches interaction of ontologies of multiple data sources with the customer profile formal model too. Section 4 outlines the agent-based architecture of RS components implementing two its basic use cases that are (1) the customer profile learning and (2) recommendation related decision making use cases. Section 5 provides for related work survey with the focus on the existing ontology-based customer profile models. Conclusion describes the current progress in development of the presented components and sketches future efforts.

2 Data Set Meta-model

To demonstrate the basic paper ideas in more understandable mode, Amazon data set [1] is selected as a case study. This data set explicitly uses categorization of the domain concepts that makes it simpler to model it in terms of ontology that is widely used as a basic approach to emphasize specification of data semantics. This data set comprises several data source, deals with several domains and implicitly contains information needed to enable employment of semantic-based customer's similarity. The latter makes it possible to enrich recommendation-related decision making with additional knowledge improving the recommendation quality.

The meta-model of this data set represented in terms of class diagram is depicted in Fig. 1. Its basic concept is *Product* specified in terms of *id*, *ASIN* (*Amazon Standard Identification Number*), *title*, *group* of *Products* it belongs to (*Book*, *DVD*, *Video VHS* or *Music* - see Fig. 2), *salesrank* (rate of *Product* sales), *similarid* (set of other *Product ASINs* bought together with the *Product*), *categories*. The *categories* the *Product* are given as a hierarchy of sequential nodes separated by symbol "|". *Category Id* is indicated within the squired brackets [*]. *Product* is also assigned with *customers reviews*, which attributes are *time*, *customer's Id*, *rating value*, *total number of reviews*. The last attribute of the concept *Product* is *avgrating* that is averaged Product rating assigned to it by *customers*, in their *reviews*.

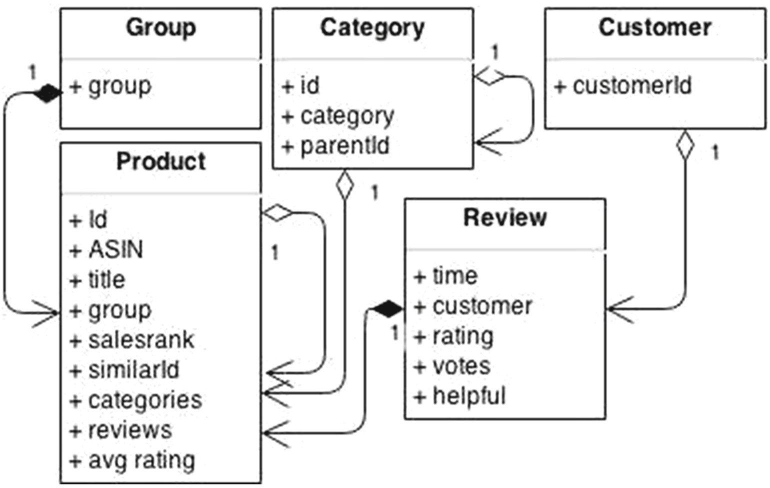

Fig. 1. Amazon data set class diagram structure

Figure 2 presents additional information about the Amazon data set structure while depicting *entity-relationship* diagram with extended information about the following concepts: *Product group categories*, *Product similarity* and customer's

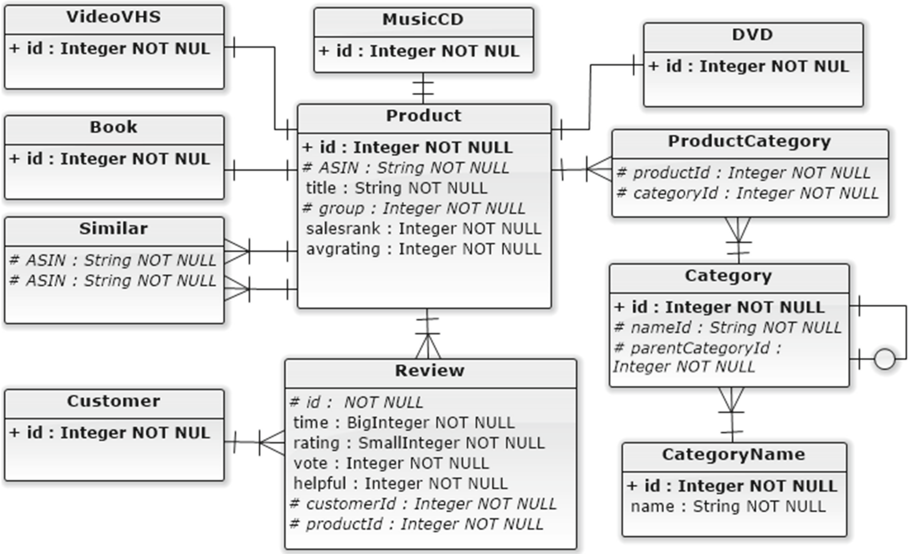

Fig. 2. Entity-relationship class diagram of the Amazon data set

reviews that can be provided for a *Product*. Figure 3 gives a shortened example of the Amazon data set record specifying an instance of the *Product* of the group *Book* and representing the instance properties related to *categorization* and *similarity*.

3 Structured Representation of Customer Profile

Ontology categorization presenting concept hierarchy is the first class component of any ontology. Let us note that each *Product instance* can belong to several categories (see, for example, Fig. 3).

What is important, that categorization of the ontology concepts can be introduced in many different ways. For example, some, perhaps, artificially introduced subcategories can be of great importance for practical purposes. One of such examples can be seen in Amazon data set ontology fragment shown in Fig. 4. Each node of this fragment represents a subclass of movies. It is worth to note that each node of the ontology hierarchy can be uniquely mapped a subset of *Product* items (a subset of particular *Movies*, in Fig. 4) possessing corresponding properties (in Fig. 4 these properties shown inside the blocks).

Vice versa, let us assume that the items of *Product* are mapped to the categories introduced in ontology (like the one done in Fig. 4) correspond to such *Product* items that were selected and positively reviewed by the target customer. In such cases, every particular node will represent the favor customer selections that can be used as learning data set to discover the properties of the items selected by the customer and some of the discovered properties can correspond to a particular customer interest. The node corresponding to the favorite customer selections with explicitly indicated common properties discovered via learning can be interpreted as a particular *category* of the ontology. Ontology comprising such node-categories can be considered as a concept hierarchy presenting customer interests in structured form. Such structure would be considered as a useful variant of the customer profile. The question is how to select such subcategories of *Product* that fit the customer interest structure in the best way.

```
Id:   15
ASIN: 1559362022
title: Wake Up and Smell the Coffee
group: Book
similar: 5 1559360968 1559361247 1559360828 1559361018
        0743214552
categories: 3
   |Books[283155]|Subjects[1000]|Literature & Fiction [17]
   |Drama[2159]|United States[2160]
   |Books[283155]|Subjects[1000]|Arts& Photography[1]|
   Performing Arts [521000]|Theater[2154]|General[2218]
   |Books[283155]|Subjects[1000]|Literature & Fiction[17]|
   Authors, A-Z[70021]|( B )[70023]|Bogosian, Eric[70116]
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Fig. 3. An example of the Amazon data set record specifying an instance of the *Product* of the group *Book* concerning with *categorization* and *similarity*

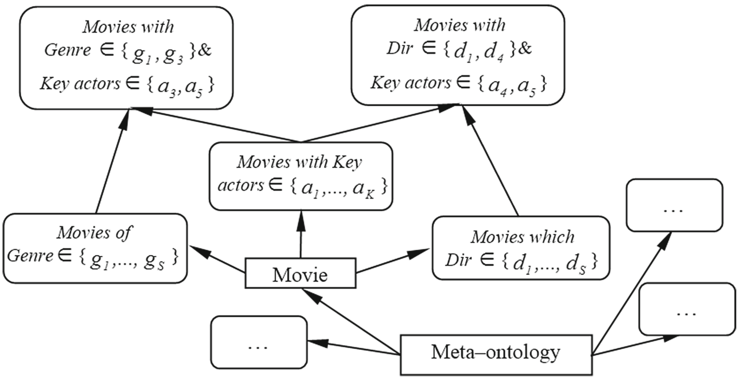

Fig. 4. Customer-profile-oriented ontology hierarchy for concept *Movie*

Fortunately, this task is not new. Let us remind that the routine subtask of Machine learning that is selection of informative features if successfully solved results in a set of features and a quality measure of each such feature is well known measure called *coverage*. At that, usual requirement to the found set of the features is that the found features together have to provide for coverage of all learning data instances. A peculiarity of the learning task formulated in previous paragraph, in comparison with the general case, is that the features in question have to be presented in a special form: they have to be specified in terms of predicates $P_S(x_{i_1} \in \widetilde{X}_{i_1}, \ldots, x_{i_k} \in \widetilde{X}_{i_k})$, where $x_{i_1}, \ldots, x_{i_k}$ – particular properties of the concept *Product*, $\widetilde{X}_{i_1}, \ldots, \widetilde{X}_{i_k}$ – sub-domains of the above properties domains, and predicates $P_S(x_{i_1} \in \widetilde{X}_{i_1}, \ldots, x_{i_k} \in \widetilde{X}_{i_k})$ take the value *true* if and only if the membership indicated in the parenthesis is held.

Thus, the conclusion resulting from the above text is that if the customer interests are expressed in terms of a set of predicates $P_S(x_{i_1} \in \widetilde{X}_{i_1}, \ldots, x_{i_k} \in \widetilde{X}_{i_k})$ then the customer interests are specified in term of *structured specific ontology* sub-categories. As a result, they are clearly interpretable in terms of ontology concepts and their attributes are given as some statements about *Product* properties. In this case, the remaining problem is whether a Machine learning technique that is capable to discover knowledge representing formally customer interests in terms of predicates $P_S(x_{i_1} \in \widetilde{X}_{i_1}, \ldots, x_{i_k} \in \widetilde{X}_{i_k})$ exists. The answer on this question is positive: a variant of such a Machine learning technique was proposed in [6]. Since the description of this technique is out of the paper scope, it is omitted here and the interested are referred to [6].

Hereinafter, it is assumed that the *customers profile* is represented in the form of a structured subset of domain ontology concepts and looks like it is shown in the toy example depicted in Fig. 4 with each node N_S associated a set of *Product* instances that match the properties indicated by the predicate $P_S(x_{i_1} \in \widetilde{X}_{i_1}, \ldots, x_{i_k} \in \widetilde{X}_{i_k})$ mapped to the corresponding node N_S. Figure 5 extends Fig. 4 in such way while exemplifying the structure of the customers profile model considered in this paper.

Several advantages are peculiar to the proposed formal model of the customer profile. Some of them are as follows:

1. It is compact, clearly and unambiguously interpretable in semantic terms of ontology concepts: each particular interest is a subclass (a category) of the domain ontology.

2. This formal model naturally implements personalization.

3. Profiles of various customers in the same domain are presented in terns of the same concept subclasses and therefore they are simply comparable since computing a semantic similarity of a customer pair requires to compare the both profile structures and to find the set of common successors. Semantic similarity measure can be expressed in terms of relative number of common interests of a pair of customers peculiar to the *Product* item under recommendation procedure. In fact this measure should be a subject of special research and experiments.

4. Customer's profile, in fact, is represented in about actionable form: only few efforts are required to design decision making mechanism, e.g. decision tree, voting mechanism or some other one.

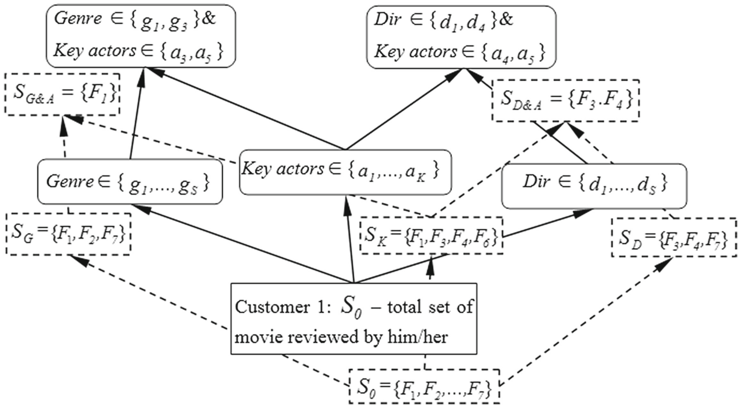

Fig. 5. Formal model of customer profile fragment: An example

5. Context can be represented via particular component of the domain ontology, and therefore, the proposed customers profile model can be naturally generalized to the case of context-aware recommendations.

6. The same concerns with the cross-domain recommendation technology: in any case, cross-domain recommendation is realistic in the cases when corresponding domains have something in common that can be expressed in terms of common concepts of both domain ontologies. Particular techniques of ontology-based cross-domain decision making is a subject of a deeper research. For example, Fig. 6 represents graphically a fragment of the ontology hierarchy for *Product* of the *group Music* peculiar to a particular customer. It contains hierarchy of the nodes entitled *Comedy*. Figure 7 represents a fragment of ontology group "*Video VHS*". It also contains the nodes entitled *Comedy*. *Comedy* as a genre can be a customer interest and both ontologies (given in Figs. 6 and 7) can contain something in common, for the same particular customer.

7. Finally, information fusion from several, perhaps, distributed data sources is also naturally resolved if to use ontology as a meta-model defined on top of distributed data sources that makes it possible to use any information fusion strategy including those ones that provides for data sources with privacy preserving.

4 Agent-based Architecture for Customer Profile Learning

Two basic use cases of RS should be supported by its software components, (1) learning of customer profile and (2) producing recommendations when necessary. The basic source of the learning information is learning data set, e.g. Amazon data set [1], in this paper. The objective of learning use case is learning of the customer profile in the form outlined above. One of the existing technologies proposed in [6] comprises three basis steps. In the first step, the predicates $P_S(x_{i_1} \in \widetilde{X}_{i_1}, \ldots, x_{i_k} \in \widetilde{X}_{i_k})$ are computed and filtered using Naive Bayes procedure. The result of this step is the set of association classification rules $P_S^k(x_{i_1} \in \widetilde{X}_{i_1}, \ldots, x_{i_k} \in \widetilde{X}_{i_k}) \to \omega_k$, where S is the predicate index, k is the index of target variable ω_k that is (discrete) rating of the recommendation regarding input *Product* item.

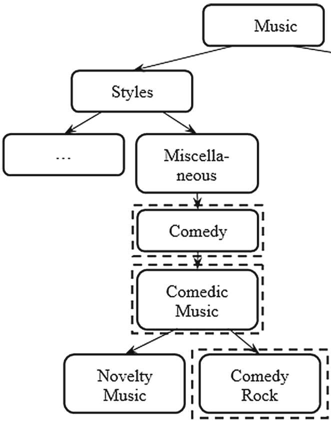

Fig. 6. Fragment of the ontology hierarchy for *Product* of the *group Music*

At the second step, causal analytics-based approach as applied to the aforementioned association rules intends to detect those of rules that correspond to the causal dependencies between premises P_S^k and consequences ω_k, $S = 1, \ldots, S_k$, $k = 1, \ldots, m$. After filtering the causal rules $P_S^k \to \omega_k$ according to some criterion, the remaining set of predicates $\left\{P_S^k(x_{i_1} \in \widetilde{X}_{i_1}, \ldots, x_{i_k} \in \widetilde{X}_{i_k})\right\}\Big|_{S=1}^{S_k}\Big|_{k=1}^{m}$ for each $k = 1, \ldots, m$ forms the set of nodes (they correspond to the particular customer interests) of the domain ontology regarding every target variable ω_k. Subsequent structuring of the nodes and mapping them to the corresponding instances of the learning data set like it is shown in Fig. 5 results in getting the structured customer profiles related to every target variable ω_k, $k = 1, \ldots, m$.

The third step is development and testing of recommendation-related decision making mechanism.

Let us note that this mechanism exploits the properties of *Product* items that are in the focus of the customer interests structured as his/her profile. It forms informative aggregated feature basis for *content-based reasoning* (CBR) mechanism, in RS. Its important novelty, in comparison with the traditional CBR, is that it uses the *core propertied* of *Product* items that match the target customer *interests* expressed in semantic form as the structured set of causes determining these or those preferences of the customer.

Additional important sources of information that are capable to improve recommendations in a noticeable degree are the target customer's "friend"

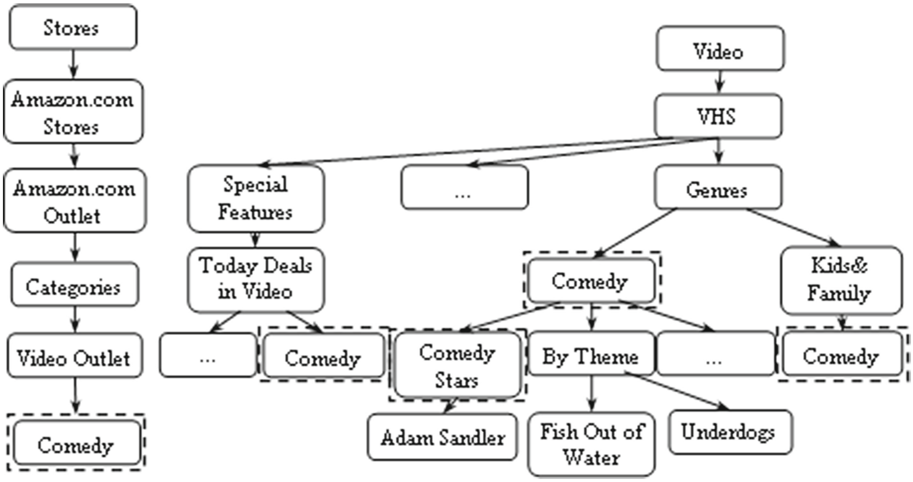

Fig. 7. Fragment of the ontology hierarchy of the Amazon data set group *Video VHS*

community profiles and similarity measures of them regarding to the target customer profile matched to the formers. If to have in mind that the customers are united within "friend" community groups in a social network then it is reasonable to search for customers of similar profile among the friends of the same interest group. In general case, the semantically similar customers can be found too if similarity measure is common interest-based. It is well known that customer similarity-based recommendations are implemented by collaborative filtering (CF) approach. The novelty of the CF in the case of ontology-based similarity measure is that, in it, similarity measure is expressed in terms of customer interests that explicitly take into account the causes determining customer selections in the past.

The roles of the agents in the semantic versions of CBF and CF introduced above are different. What concerns CBF-related learning, this mechanism can be realized using one of the many existing learning classification mechanisms, e.g., decision tree designed in a way (e.g. using some C4.5 like mechanism [12]), a variant of voting [8], boosting [4] or some other approach [5]. In the learning use case of CBF mechanism, learning agent uses only information associated with the target customer the agent assists to and it does not need to use data set instances or ontology connected to another customers. This agent, nevertheless, has to operate with various data sources while preserving privacy. Figure 8 presents a variant of agent-based CBF architecture with collaboration of the agents responsible for information fusion, in learning use case, while preserving privacy. The particular agent interaction protocol, in this use case, should depend on the information fusion strategy selected. One of such strategy is decision fusion, for example, that is well investigated in the information fusion research community.

Other situation occurs in the case dealing with learning of semantic CF filtering-based mechanism. Here, like CBF case, several agents have to assist

RS in learning use case to work with multiple data sources, if any. Additional functions of agents are associated with on-line search for similar customers and corresponding similarity measures. The first distinctive feature of these functions is that they have to operate online because selection of similar customers and computing semantic similarity measures depends on particular *Product* item to be rated. The second feature is that it has to intensively cooperate with the analogous agents of other customers. The latter is especially important due to privacy-related constraints. To support these interactions, a specific dedicated protocol has to be developed. This task is in progress and also a subject of the forthcoming research.

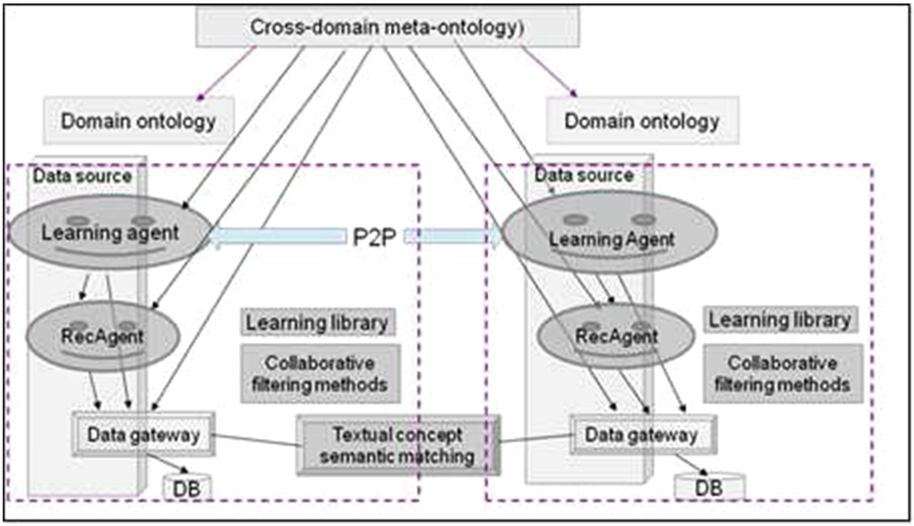

Fig. 8. Agent-based architecture of learning recommendation system

5 Related Works

Two main classes of approaches to representation of customer interests and preferences in RS are proposed:

– in the form of a simple vector of customer's items ratings (explicitly specified or calculated); this form of customer profile is peculiar to the recommending systems of the 1st and the 2d generations;
– in the form of a customer profile model focused on personalization with explicitly-expressed semantics of the profile attributes. As a rule, such profiles are supported with domain or multi-domain ontology and comprise personal customer attributes (e.g., age, gender, origin), his/her context-aware

intentions (looking items to buy, e.g. New Year gifts), interests (e.g., sports, entertainment, books, software), social connections (e.g., family, friends in Facebook), etc. Customer profile of this type is usually structured in more sophisticated form than simple vector of attributes. Corresponding RS are classified as RS of the 3G.

In the short analysis of the related works below, only the last type of customer profiles is considered. The common property of such profiles is explicit exploitation of domain ontology. Various variants of such customer profiles are proposed and tested to date.

Reference [15] focuses on personalization of customer profile expressed in terms of concepts of predefined ontology. Authors use the Open Directory Project concept hierarchy (ODP, 2002) associated with manually classified web pages as the basis of their reference ontology. The profile is built manually using keyword vectors of the visited web pages. Classification of the web pages consists in comparison of the vector created for the web page with each concepts vector using the cosine similarity measure. K-nearest-neighbors technique is used to find the top matches. The customer profile is represented as the total weight and number of pages (documents) associated with each concept in the ontology. Most of the modern requirements to the customer profile properties mentioned in Sect. 3 are not discussed in this paper.

Reference [9] explores an ontological model-based customer profiling as applied to recommender systems intended to online recommend academic research papers. The latter are classified using ontological classes and collaborative filtering. Customer interest profile is represented in term of research paper topic ontology developed in the framework of AKT initiative [10]. Ontological relationships between topics of interest enable inference of other topics of customer interest including those that have been not browsed by him/her explicitly so far.

Reference [3] proposes customer-profiling model covering multiple domains while assuming that each domain is specified in terms of ontology. It aims to overcome the drawbacks of existing customer profile models, which, as a rule, do not involve context into recommendation while accentuating mostly the keyword-based matching approach, but not the semantic matching supported by single domain ontology. The authors note that these approaches can result in inconsistent recommendations. The paper purposes CORe-Context-aware, Ontology-based Recommender system framework which motivation is to work with multiple domains and attract context as an important components needed for accurate and more personalized recommendations. "Another novelty of COReS is the adoption of compartmentalize the customer profile according to different domains, selected in time of prediction, based on the customers context", the authors wrote. Unfortunately, this paper does not propose algorithmic or software means that could support automatic generation of multi-domain ontology-based customer profile with the documents mapped to the corresponding ontology concepts. Additionally it considers multi-domain aspects of the customer profile, but not cross-domain one that is much more demanded. It also does not assume collaborative comparative use of different customer profiles making it possible to semantic-focused computing of customer similarity measure thus enabling a new class of collaborative filtering models and mechanisms.

Reference [16] proposes a customer profiling model for multi-source data (Twitter, Facebook, LinkedIn and homepages, in particular). Customer interests are expressed in terms of ontology concepts. Ontology is used to establish various interconnections among different customer interests represented in multiple data sources with different granularities. Ontology set up on top of multi-source data is also used to infer implicit customer interests by reasoning on ontology-based interest hierarchy. In general, the paper sketches the potential directions and perspectives of rich semantic-oriented customer profile model, but no more, since it demonstrates basic ideas on too simplified examples. It is not clear how adequately the proposed ideas can be used in the applications of about practical scale.

Reference [11] considers twitter-based modeling of personalized customer interests and intentions through profiling. It proposes an inference procedure intended for customer profile and "introduces a scalable and automated technique based on extracting customers URLs", the authors stated. Peculiarity of the proposed technique is that it exploits the existing domain categorization of web sites to find the categories of customer interests and intentions constituting his/her ontology-based profile that enables dynamic evolving of the profile. General characteristics of the customer, e.g. age, location, profession, etc. included into his/her profile are aimed to improve personalization of the latter.

Reference [17] proposes a customer profile vocabulary specified in terms of RDF language as a method to provide, for customer profile consistency with regard to several domains within a Web search class of applications. The idea is to use such a customer profile as additional constraint together with the vocabulary of the customer query ("interests-based query refinement"), while taking into account that the latter, as a rule, is too vague and if used alone leads to very many unnecessary documents. The paper considers an extended definition of customer interest that includes not only the interest concept itself ("the subject that an agent wants to get to know, learn about, or be involved in", according to the authors definition), but also add to it some attributes representing context, time, for example. In fact, this definition assumes the development of a standard vocabulary of the interest concepts assigned a fixed set of attributes, as well as some context-related attributes. But, the first, this is not feasible now to develop such vocabulary covering all types of interests, the second, the paper ignores an important component of customer profile specification that is a structure existing over the customer interests. If fact, the paper results are applicable to web search only.

Reference [14] motivates the use of customer interest ontology by the necessity to cover the lack of semantic information to build personalized customer profile that is dynamically changing over time. The collaborative recommendation is based on semantic similarity of the target customer with other customers and on their opinions regarding an item under recommendation procedure. Based on customer interest ontology, the paper proposes customer interest model and algorithm performing its automatic update. Hierarchical structuring of customer interest is claimed as a goal of future research.

Reference [2] presents an enrichment of the customer profile ontology with tags. It proposes a method for the unification of tags with ontologies by "grounding tags to a shared representation in the form of Wordnet and Wikipedia". It incorporates tagging history of a customer into his/her ontological profiles via matching tags with ontology concepts. This model looks as a perspective way to extend the number of information sources involved into customer profile design.

Additional useful information on the discussed topic can be found in [7,13], etc.

6 Conclusion

The paper proposes an ontology-based customer profile model that should meet the current requirements to the capabilities of 3G recommending systems concerning with their multi-source cross-domain natures and focus on clear semantics of customer interests. Specific ontology concepts constituting customer profile as a structured set of customer interests are got through special learning procedure which basic procedures are feature aggregation, filtering and causal analysis. These procedures were developed and tested in the previous works of the paper authors [6]. The paper also attracts attention to the specific issues of the implementation of the multi-source data fusion peculiar to 3G recommending systems under privacy preserving constraints. Multi-agent architecture intended to cope with the aforementioned problem is outlined. In general, the paper highlights the basic conceptual issues of the 3G recommending systems model, its basic components and their agent-based interaction in customer profile learning use case. Future efforts should be focused on 3G recommending systems design and implementation issues, which will unavoidably put forward new unexpected problems.

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