A Trust-based Social Recommender for Teachers

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Abstract. Online communities and networked learning provide teachers with social learning opportunities to interact and collaborate with others in order to develop their personal and professional skills. In this paper, Learning Networks are presented as an open infrastructure to provide teachers with such learning opportunities. However, with the large number of learning resources produced everyday, teachers need to find out what are the most suitable resources for them. In this paper, recommender systems are introduced as a potential solution to address this issue. Unfortunately, most of the educational recommender systems cannot make accurate recommendations due to the sparsity of the educational datasets. To overcome this problem, we propose a research approach that describes how one may take advantage of the social data which are obtained from monitoring the activities of teachers while they are using our social recommender.
Keywords. Learning Network, recommender system, teacher, social data, social networks, sparsity, trust

1 Introduction

The Internet provides teachers with a social space to interact and access resources in the form of either knowledge content or knowledgeable people outside their school [28], [13]. Online learning communities and networked learning are increasingly accepted by teachers as opportunities to continuously develop their personal and professional skills [11], [7]. Learning Networks (LN) are online social networks that follow the main goal of professional online communities for lifelong learners such as teachers, who need continuous support and guidance to develop themselves both personally and professionally [29]. Learning Networks can provide teachers with an open infrastructure not only to share, annotate, rate and tag content, but also to exchange knowledge and experience with the other members of the LN. Learning from others in a social context is a promising form of learning, which motivates learners to continuously learn and exchange knowledge. Research has shown the positive effects of social learning [31], [8], [4]. In this paper, we discuss how one may take advantage of LNs as an infrastructure to support teachers as lifelong learners.

With the increasing amount of user-generated content produced everyday in the form of learning resources, videos, discussion forums, blogs, etc., it becomes ever more difficult for teachers to find the most suitable content for their needs. Moreover, to support social learning, teachers need to be supported to find the most suitable people who can help them to learn more effectively by sharing knowledge and experiences [31]. Generally speaking, recommender systems have emerged as a practical approach to provide a user with the most suitable objects based on their past behaviour. Recommender systems have become popular because of their successful applications in the e-commerce world such as in Amazon[1] and eBay[2]. Fortunately, they can be adjusted to be used also in the educational domain [10], [21].

In general, recommender systems suggest items to a target user. They do so based on the similarity between an item's content description and the user's preferences model (content-based); or they measure similarity between user profiles to predict an item's rating for a target user based on the rating history of the users who are similar to the target user (collaborative filtering). In this research, we take advantage of collaborative filtering methods as we mainly focus on the interactions and collaborations between teachers within a social environment. However, it is too difficult to compute similarity of user profiles when there is no common set of ratings between the users or when there are too little rating data available; this is known as the *sparsity problem*. Educational datasets suffer from this problem more often than commercial datasets [32]. Therefore, we need to find ways to overcome the sparsity problem in educational datasets if it is our aim to enhance the performance of recommender systems in learning. Social trust has been introduced to many recommender systems as a response to the sparsity problem [14], [36], [16], [19], [17]. Ziegler and Golbeck [36] show a strong connection between trust and similarity between users. In general, users prefer to receive recommendations from the people they trust. Golbeck [14] shows that trust captures not only simple overall similarity between users but also other features of the profile similarity

In teachers' communities, teachers can perhaps be supported to find trustworthy resources as proxies for reliable sources of information. Such trustworthy resources enable teachers to feel more comfortable to share and interact within a closed and trustful community. To achieve this, we follow a trust-based recommender system proposed by [12] to create trust relationships between users based on the rating information of user profile and item profile. Fazeli et al. [12] proposed a concept called T-index to measure trustworthiness of users in order to improve the process of finding the nearest neighbours. The T-index is inspired on the H-index, which is used to evaluate the publications of an author. The higher the T-index value of a user, the more trustworthy the user becomes. Fazeli et al. showed how the T-index improves structure of a generated trust network of users by creating connections to more trustworthy users [12]. They computed the trust values between users based on the ratings users gave to the items in their system. Although ratings' information is one of the examples of users' activities within a social environment, other social activities of users also can be worthwhile and should not be ignored up front. In general, the social activities of users describe each action of users within a social environment, for instance browsing a Web page, bookmarking, tagging, making a comment, giving rating, etc.

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1 http://www.amazon.com
2 http://www.ebay.com

We refer to the data that comes from the social activities of users, as "social data". In this research, we aim to enhance the existing trust-based recommender of Fazeli et al. [12] by social data which are obtained from monitoring the activities of teachers while they are using our social recommender.

Therefore, the first research question is:

RQ1: How can the sparsity problem within educational datasets be solved by using inter-user trust relationships which originally come from the social data of users?

Moreover, we aim to investigate the evolution of LNs while we collect social data from users. Therefore, we need to study the structure of LNs for teachers to show how using social data can help to cluster teachers more precisely and as a result to find the most suitable content or people for their needs. So, the second research question is:

RQ2: How can teachers' networks be made to evolve by the use of social data?

In the following section, we present the research methodology used to address these two questions.

2 Proposed research

Our main objective is to support teachers to find the most suitable content or people and do so more effectively. The idea is that through finding suitable peers and content they will be better able to develop their personal and professional skills.

In order to achieve this goal, we follow the methodology described by [22] for recommender systems in TEL. We extend the methodology by first conducting an interview study with teachers. The research work, therefore, consists of four steps: 1. Requirement analysis (literature review and interview study), 2. Dataset-driven study , 3. User evaluation study, 4. Pilot study. We will describe each step in terms of its main goal, used methods, and the expected outcomes, in the following subsections.

2.1 Requirement analysis (literature review and interview study)

- **Goal.** Besides a literature study on the issues and challenges teacher often face, we organized interview group sessions with teachers and collected information from them in order to investigate their main needs and requirements.
- **Method.** The interview group session was conducted using the nominal group technique (NGT) [9]; the session took almost 2 hours and 45 minutes. The participants were 18 teachers (novices, experts, mentors and supervising teachers) from different schools in the Limburg area, the Netherlands, invited by Fontys Hogeschool.
- **Description.** During the session, the participants were asked to write down their ideas about the following question: "What kind of support do you need to provide innovative teaching at your school?" Then, we asked them to discuss the ideas gen-

erated and finally, to rank the ideas based on a five-point Likert scale (1 for the least interesting idea and 5 for the most interesting one). The teachers generated 121 ideas in total. The clustering was done during the session by the researchers (the alternative, to have the teachers do it, was rejected because of time limitations). After the session, we invited the teachers to cluster the ideas in a Web-based application called Websort[3]. The data are still being analysed.
- **Expected outcomes.** An inventory of teachers' needs and requirements will be the outcome of this step. This inventory list will be used to as an input to design a recommender system which suits teachers' needs the best.

2.2 Dataset-driven study

- **Goal.** The main goal is to validate the framework we propose which presents the important characteristics of a recommender system to be designed for teachers. We will elaborate the framework in details in Section 3.
- **Method.** An offline empirical study of different algorithms on a selected set of representative datasets is to be conducted. The offline experiments (data study) on educational datasets will be in terms of the popular metrics often used to evaluate the performance of recommender systems.
- **Variables to be measured.** Prediction accuracy and coverage of the generated recommendations are the variables to be measured in this step.
- **Description.** Based on the literature review and the interview study, we present a framework to identify the suitable recommender systems' strategies to be applied for our target users which helped us to make an effective selection of the available educational datasets. The selected educational datasets for teachers to be studied are TravelWell [33], MACE[4], Organic.Edunet[5], TELeurope[6], OpenScout[7], digischool[8] and eTwinning[9].
- **Expected outcomes.** Initial results will indicate which of the recommender system algorithms suits teachers best and if the trust-based recommender system can help to deal with the sparse data in the used datasets.

2.3 User evaluation study

- **Goal.** The goal is to study usability of the prototype by evaluating users' satisfaction.
- **Method.** The experiment will be done by a questionnaire through which end-users will be asked to provide feedback on the prototype.

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3 http://uxpunk.com/websort/
4 http://portal.mace-project.eu
5 http://portal.organic-edunet.eu
6 http://www.teleurope.eu/
7 http://www.openscout.net
8 http://www2.digischool.nl/leerling/vo
9 http://www.etwinning.net/en/pub/index.htm

- **Variables to be measured.** User evaluation will be in terms of interestingness (how much the end-users find the recommended content or people interesting) and value-addedness (how recommended content or people can help users to gain new knowledge or improve their current knowledge) [32].
- **Description.** Based on the outcomes, the prototype will be customized and improved so as to be able to deploy an improved release in a pilot study.
- **Expected outcomes.** Initial feedback by end-users on usability of the prototype is the outcome we expect.

2.4 Pilot study

- **Goal**. We aim to deploy the final release to test it under realistic and normal operational conditions with the end-users.
- **Method.** We compare the performance of a proposed recommender system based on our presented framework with classical collaborative filtering algorithms. Furthermore, we aim to study the structure of the teachers' networks to investigate how networks of teachers will evolve by use of social data. To evaluate the effectiveness of the proposed recommender system, we will compare the results in terms of total number of learning objects which have been visited, bookmarked, rated, etc. for two groups of users:
  - Those who are aided by recommender systems to access learning objects
  - Those who access learning objects directly from the repository, without the help of a recommender system.
- **Variables to be measured.** We will measure prediction accuracy and coverage of the generated recommendations, effectiveness in terms of total number of visited, bookmarked, or rated learning objects, as well as Indegree distribution used to study how the structure of the networks changes. For a node on a network, Indegree describes the number of coming edges (or relationships) to the node.
- **Expected outcomes.** We expect to obtain empirical data on prediction accuracy and coverage, to validate whether our proposed recommender system outperforms the classical CF algorithms. Another outcome will be the visualization of teachers' networks, to show how the network's structure evolves when relying on social data.

Having given an overview of the research method, we will now present the state-of-the-art in recommender systems to allow us to explore the characteristics which should be taken into account to design a suitable recommender system for teachers.

3 State-of-the-art

Several reviews exist which detail how to study and classify recommender systems in terms of recommendation techniques, tasks, delivery mode, etc [22]. However, each of these reviews focuses only on some of the dimensions to classify recommender systems and none of them present an integrated framework for the classification of recommender systems. Manouselis and Costopoulou [22] propose a framework to categorize the dimensions of recommender systems, which were identified in the previous studies. We will use this framework to investigate the characteristics that should be considered to design a recommender system for teachers. As shown in Figure 1, the proposed framework consists of five main categories of characteristics: Supported tasks, User model, Domain model, Personalization, and Operation. In the rest of this section, we will introduce each of the characteristics briefly and we will conclude how the resulting framework could be applied to a recommender system for teachers.

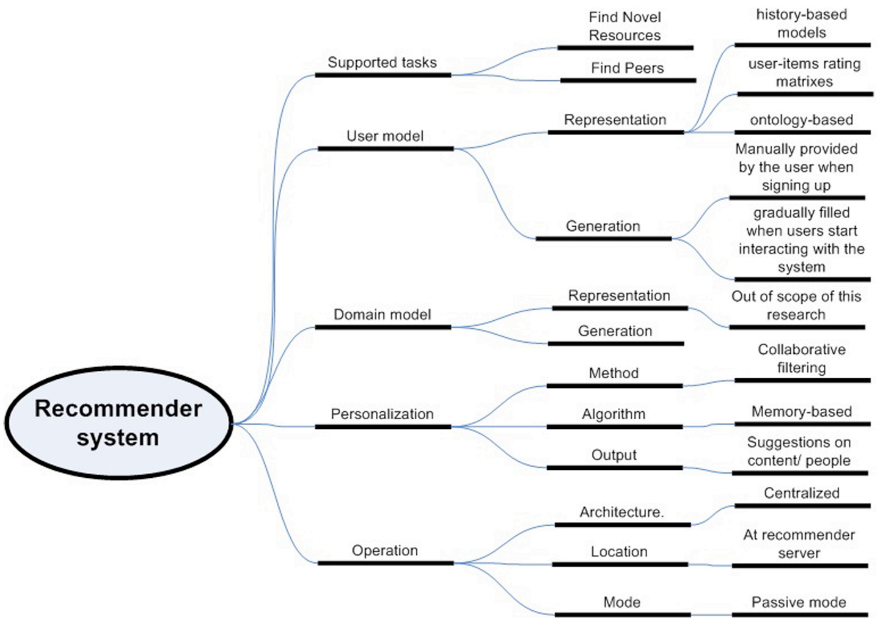

Fig. 1. A proposed social recommender system for teachers

3.1 Supported Tasks

As mentioned before, teachers need to keep informed about the resources which can inspire them to deal with the issues they face in their job. So, we aim to support teachers to *Find Novel Resources* which are suitable for them based on their profile history. Most of the recommender systems in the educational domain have been designed to support this task [25], [18], [24], [31], [10]. For more examples, refer to the book by Manouselis et al. [22]. Moreover, teachers need to be supported to *Find Peers* who can be trusted to share their concerns with them and to receive help from them, so-called trustworthy peers. According to an extensive overview of the recommender systems in the Technology Enhanced Learning (TEL) field provided by Manouselis et al. [22], only few of the recommender systems aim to support this task [25], [1].

3.2 User model

We represent user profiles for teachers by history-based models and user-item matrix which mainly focus on the past activities of the users such as ratings information [25], [18], [10], [22]. Furthermore, we aim to create user profiles based on ontology to provide more interoperability and openness among different platforms. Therefore, we are going to use ontology to model the relationships between teachers in social networks [12], [14]. The user profiles for teachers are generated based on the information provided by the users when they themselves fill in a registration form with their personal information (name, surname, email, etc.) and professional information (teaching subject, interests, background knowledge, etc.). We refer to this part of the user profile as *static data* as it can be edited manually by the users anytime they want to. The other part of the user profiles contains *recommendation data.* It will be updated by our system as soon as teachers start interacting with the system. Since our main objective is to support teachers with a recommender system in the educational domain, we have to take into account the teachers' characteristics. So, to create a user model for teachers, we need to consider both actions of teachers and context variables in the TEL field [34]. Verbert et al. [34] describe the main characteristics that are to be considered for users in an educational context, such as knowledge level, interests, goals and tasks, and background knowledge, in addition to the data regarding users' actions in terms of type and result of actions and the context in which an action has been taken.

As indicated, we intend to take advantage of social data of users to deal with the sparsity problem. To do so, we keep track of users' actions within our system, so-called social activities, when they rate, tag, and bookmark content. In this way, the recommendations will be generated and improved based on the recorded actions of teachers while they interact with our system. As mentioned before, social data originally comes from these recorded actions of users (teachers). To capture their social data, we need to follow a standard specification to store and maintain their actions. Several standard specifications to describe social data of users and guarantee their interoperability exist. They are:

- **FOAF.** The FOAF (Friend-of-a-Friend) vocabulary [3] describes user's information and their social connections through concepts and properties in form of an ontology using Semantic Web technologies [14]. The FOAF Vocabulary describes personal information and social relationships. The FOAF Vocabulary shows basic information of users (FOAF Basics) such as name, surname and also personal information about the people that a user "knows" and its interest area (Personal Info). In this research, we could extend the FOAF ontology to describe user profiles and to model the social relationships between teachers by the concept of *FOAF:agent.*
- **CAM.** Contextualized Attention Metadata (CAM) is a format to capture observations about users' activities with any kind of tool [35]. A CAM schema aims to store whatever has attracted users' attention while the users are working with the tool. It also stores users' interaction with the tool such as rating, tagging, etc. A CAM schema records an event and its details when a user performs an action within a tool. The metadata stored in the CAM format describe all type of users' feedback and, therefore, can be used to make recommendations for the users. We could

make use of the CAM schema to capture the users' activities within our system and as a result, to extract the social data of users in order to create user profiles.

Annotation scheme. In the context of Organic.Edunet[10], Manouselis and Vuorikari [20] developed a model to represent and store users' feedback including rating, tagging, reviewing, etc. in a structured, interoperable and reusable format. This model is based on the CAM format. Manouselis and Vuorikari called it an annotation scheme and proposed it as a structured and interoperable format to be used to transfer the social data of users between heterogeneous systems. We could take advantage of the annotation scheme to describe social data of users within our system.

3.3 Domain model

Items to be presented to teachers need to be represented somehow and need to be generated before they can be presented. This task is out of scope for the present research project. It will, parenthetically, be taken up by the Open Discovery Space project[11] which aims to represent learning objects in the form of an integrated object repository containing several collections of learning objects which are hosted by the ARIADNE[12] infrastructure.

3.4 Personalization

Method. In general, and as we already pointed out in Section 1, there are two main types of algorithms used in recommender systems: content-based and collaborative filtering. Content-based algorithms compare the description of an item with representations of users' interests. Amazon is a good example of such a recommender system, which provides a so-called 'favorites' feature to represent the preferred items by users. The 'favorites' are introduced as the content-based part of user profiles, which are either manually provided by a user or are calculated based on purchase history of the user [23]. As content-based algorithms make recommendations for a user only based on the user's interests individually, the user is less likely to find novel items which might be interesting to the user [6]. Collaborative Filtering (CF) is another type of recommender systems which purely depends on opinions and ratings of users instead of actual content descriptions. CF algorithms search for like-minded users that are introduced as neighbourhoods and they predict an item's rating for a target user based on collected ratings of the user's neighbours [27]. They recommend a target user top-N recommended neighbours and/or items. Traditional CF algorithms form the neighbourhoods based on similarity between user profiles [25], [24], [10], [21], [33].

As mentioned before, traditional CF algorithms suffer from the sparsity problem if too little rating information is available to compute similarity between users. Social

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[10] http://portal.organic-edunet.eu/

[11] Open Discovery Space is a 7th framework European project partly sponsored the presented research work in this document.

[12] http://www.ariadne-eu.org/repositories

trust has emerged as a solution to the sparsity problem in many recommender systems [14], [36], [16], [19], [17]. In the research area of recommender systems, trustworthy users have been introduced as like-minded users and thus, trust originates from similarity between users. However, assuming that trust is transitive (if A trusts B and B trusts C, then A trusts C), we may find a relationship between two users who have no common set of items but do have friends in common. Suppose we have two users: Alice and Carol who have no rated set of items in common. Therefore, it is not possible to compute similarity between them. As a result, there will no direct relationship between Alice and Carol even though they are already indirectly connected through another user whose name is Bob. In this case, the inter-user trust phenomena helps us to infer a relationship between Alice and Carol through their common friend Bob because if Alice trusts Bob in his recommendations on papers and Bob also trusts Carol in the same way then, Alice can trust Carol in her recommendations on papers. This is how we define "trust" in this research work. Therefore, we form neighbourhoods based on the trust relationships between users and we introduce the top-N neighbours, commonly used in CF, as the most trustworthy users for a target user. To do so, we are going to adjust an existing trust-based recommender system proposed by Fazeli et al. [12] to make it suitable for an educational setting, particularly for teachers. Furthermore, we aim to take advantage of social data of users described in Section 3.2, to boost the performance of our proposed recommender system for teachers.

Type and Technique. CF methods are often categorized according to type or technique. Type refers to memory-based and model-based algorithms; and technique refers to user-based, item-based, and attribute-based approaches [26], [28]. Model-based algorithms use probabilistic approaches to develop model of a user based on the user's history and profile. Examples of model-based algorithms are Bayesian networks, neural networks, and algebraic approaches such as eigenvectors [16]. Although these algorithms are faster than memory-based algorithms, they require a full set of users' preferences to develop user models; such a set is often not available. Moreover, model-based algorithms are often very costly for learning and updating phases. Instead, memory-based algorithms are quite straightforward to use. They find correlations between users based on statistical techniques for measuring similarity such as Pearson correlations or Cosine similarities [2]. In this research, we aim to use memory-based CF algorithms to recommend teachers the most suitable content or people, based on the user-based techniques which focus on the similarity between users in order to make recommendations [28].

Output. Most of the recommender systems generate recommendations in the form of suggestions on content or people, or sometimes ratings [25], [10], [1]. Another common output of recommender systems is predictions of a rating value that a user would give to an item [28], [33].

3.5 Operation

In this research, we intend to follow a centralized architecture, in which a central recommender server provides access to a single learning object repository. The recommendations are to be made at the recommender server (location) and are to be sent to the teachers as part of natural interactions of the users within our system, for example when the user browses a page or rates an item. In this way, teachers do not need to ask to receive recommendations explicitly (passive mode) [28].

4 Conclusion and further work

In this paper, we described why teachers need to be supported to find the most suitable content or people for their needs and we introduced recommender systems as a potential solution to address this issue. We also argued that we need to overcome the sparsity problem when we aim to enhance the performance of recommender systems in the educational domain and particularly for teachers. Therefore, we presented our research questions and research method that mainly focus on a solution to tackle the sparsity problem. As part of our proposed research based on the literature study, we proposed a framework that explores the main characteristics required to design a recommender system approach that suits teachers' needs the best. To validate this framework, we already started to set up an offline empirical study to test different algorithms of recommender systems on the selected datasets. As for the requirement analysis, an interview study has been conducted for 18 teachers from the Netherlands who already have been invited to cluster their ideas by Websort, following up the group session we had with them (described in Section 2.1). Furthermore, we took advantage of the Open Discovery Space Summer School in Greece, in July 2012 to involve more teachers in the Websort study. As a result, we now have an extensive analysis of the requirements for teachers all over the Europe. We are currently investigating the data and will present outcomes of the study in a special issue of the RecSysTEL workshop that will be published by Springer.

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