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Dialogue of Cultures - Culture of Dialogue: from Conflicting to Understanding

A RECOMMENDATION SYSTEM FOR BUILDING SCHOOL TEACHERS' MULTIDISCIPLINARY SKILLS

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Abstract

Educational systems are in serious need of personalized platforms, that could help to build students' multidisciplinary skills. A recommendation system focused on multidisciplinary learning objects could be a solution to the issue. Moscow electronic school repository is analyzed and patterns of its users' behaviors are described. Those patterns are observed based on the character and structure of actions available to the users, such as creating, copying, using, accessing, and viewing learning objects. The platform users constitute a network community, using similar objects and showing similar interests and thus building network relationships. These networks can be analyzed both at the macro and micro levels, thus visualizing a personal profile of a user in the system. Data analysis showed 7 clusters of users, most of who are not very active, while a moderate number of them exhibit so-called lurking behavior. They look through the learning resources, sometimes use them, but seldom create their own content. Our research found that a trend to create multidisciplinary objects is observed among active users, while lurkers are likely to create mostly monodisciplinary objects. The ratio of multidisciplinary objects can be increased by supporting delurking behaviors among users. Our findings can be useful both for educators and developers of platform learning solutions.

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Keywords: Recommendation system, repository, learning analytics, lurkers.

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1. Introduction

Recommender systems today are one of the most demanded types of information solutions. It is a result of ever-growing information increase observed in multiple industries including education. The rise of educational recommender systems is closely connected with the evolution of learning objects repositories, which started in the 2000-s when the US Universities started to share their learning content in the public domain as part of Open Courseware initiative. So, it was recognized that for Universities it is more viable to share their learning resources and attract new students and gain publicity rather than conceal and protect them by copyright law. Although, while open educational resources were growing, a new issue of navigating in this abyss emerged.

Learning objects that populate public repositories count in tens and hundreds of thousands. Thus, the MERLOT repository contains over 20000 objects and has 70000 users, OER Commons over 18000 resources. Schoolnet Learning Resource Exchange has over 43000 resources from 25000 providers (Drachsler et al., 2015; Manouselis et al., 2013). In this context, an impressive undertaking in this area is the Moscow Electronic School (MES) learning repository with more than 1 650 000 scenarios and 100 000 users. The total number of learning objects, including audio and video files exceeds 2000000 items.

Still, the search of the desired learning object in a repository is a complicated research task, due to multiple dimensions that should be taken into the consideration, such as the students' age group, proficiency level, the subject taught, comprehension preferences, etc. so purpose-built tools and services are required to find an adequate solution to it (Goga et al., 2015). Also, the learning objects tend to have similar names and keywords, so the recommender system should be well-calibrated to meet specific user's needs and ambitions in their current, ad hoc situation. While the number of electronic learning platform scenarios increases, a more technologically adequate solution is required.

Our work is aimed at building a recommendation system based on users' behaviors, which will recommend multidisciplinary learning objects to teachers. This work is based on extensive data analysis and clustering approach to processing the data.

2. Problem Statement

When a teacher is looking for teaching materials he does not always know exactly what the material is supposed to look like, while the search system should know exactly what the name of the object, its author, and its unique ID are. This is where a recommender system works best, as its algorithm processes information about the users' background, affiliation with certain groups, and previous choices (Hoic-Bozic et al., 2016; Karypis, 2017; Lin et al., 2018; Obeid et al., 2018) To do so the recommendation system should be able to predict which object would satisfy the user's needs at most (Ricci et al., 2015). Depending on the type of information on the user available different types of recommendation systems are used (Burke, 2007).

Thus, collaborative filtering recommendation systems are based on the platform users' community potential. The approach assumes that if a group of users has chosen similar items in the past they act accordingly in the future as well. For example, users A and B chose similar objects from the MES repository. If later user A chooses from the repository an object which user B has not chosen yet, it will

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be recommended to user B on the assumption that users A and B have similar interests and the scenario is likely to satisfy user B's needs. The collaborative filtering mechanism is an algorithmic implementation of the "word of mouth" information spreading process based on a belief that people are more likely to make their choices depending on the opinions of those who they trust.

The collaborative filtering mechanism assumes that the rating of an object by a user will be similar to the ratings of the same item by users who are close to him according to their previous estimates. The method of K-nearest neighbors is used for predicting the estimates of an item (Ricci et al., 2015) So for building a recommendation system it is essential to divide users into groups, i.e. cluster them, so that this classification could be used for recommending MES repository learning objects on the ground of the user's belonging to a certain cluster and sharing interests of a corresponding group.

The complexity of MES repository users clustering results from their disparate participation in producing and consuming the content. The roles and functions in the users' network community are spread unevenly. The major part of the content is produced by active users, who constitute the minority of the user population. Most users remain inactive or limit their contribution by just viewing or consuming the content. In the literature on the subject this observation is known as 1-9 - 90 rule. 1% of users create content, 9 % somehow contribute, 90% passively consume (Van Mierlo, 2014). Therefore, the clustering can be reduced to defining the behavioral models of not only active users, or authors, but those who just view, "lurkers".

Most researchers agree that lurkers' key behaviors are creating little content and mostly viewing (Tagarelli & Interdonato, 2018). Lurkers still show the significant intensity and can conduct multiple activities, not leading directly to creating content, i.e. adding to bookmarks, liking, commenting, etc. (Leshed, 2005). Thus, lurkers constitute the bulk network, which serves as the basis for a healthy resource ecosystem.

Lurkers also have an important role of learners, who master skills and methods of successful participation in a community but do not feel confident enough to act independently. This understanding of the lurkers' role may be regarded as an implication of Bandura's (1962) didactic theory according to which observation is the first step in gaining skills in a new activity.

Researchers often consider network centrality, i.e. the degree in which a user connects other nodes in the network, a key parameter reflecting their activity (Tagarelli & Interdonato, 2013). Thus, the more incoming connections (followers) a user has, the more authority they have possessed, and consequently, the more attractive content they post. As measures for the authority, betweenness centrality, Page Rank, or Eigenvector centrality are used. Still, it is noted that not all these methods are equally appropriate for lurkers' behaviors measurement as for Page Rank, for example, the amount of produced information is taken into consideration, while it is noted that lurkers scarcely produce any information of their own. Therefore, a method for calculating centralities based on the network topology was designed. According to this method, lurkers are identified based on three parameters:

-Excessive content consumption. The incoming - outcoming connections ratio is significantly shifted towards incoming.

-Consumed content authority. The amount of valuable information received from neighbors. The strength of the user lurker status is proportional to the authority of neighbors.

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-Non-authoritativeness of the produced information, which manifests in a relatively small amount of generated content. The strength of the user lurker status is proportional to the lurker status of neighbors.

This approach implies building throughout the lurkers' activity social capital of the whole network because the number of people among who ideas, news, etc. are spread is a significant indicator of the network power. Moreover, this approach makes it possible to increase the user's lurking status as part of the "delurking" process.

3. Research Questions

Analysis of data, generated in the MES repository electronic system leads us to several questions, responses to which will help us to better use the system and make it a valuable resource for developing teachers' multidisciplinary skills.

-How is the MES users' variety clustered? Can the behavioral patterns defined in social networks be observed in MES learning objects repository?

-What MES users groups show readiness to create multidisciplinary objects? Is there a correlation between the user's activity and the scenarios that they create?

-Is MES users' behavior affected by network parameters? Are MES users with higher network activity more involved in producing learning content?

4. Purpose of the Study

Building multidisciplinary skills is a major route in contemporary education. Although locating resources for developing such skills is a complicated issue because teaching at the secondary level is largely a monodisciplinary process. Schools lack multidisciplinary resources, which would lead to mastering broad skills. MES repository contains several multidisciplinary resources. They differ from ordinary resources because their authors tag them with several, from 2 to 24 categories, each of them corresponding with a particular school subject.

Multidisciplinary skills can be developed through the continuous use of those learning objects and an increase in their popularity among teachers. But still, the question of teachers' motives towards the development of such objects is still open. In our work, we explore the process of multidisciplinary objects development and specific features of teachers who create them. Understanding the motives of such authors to create multidisciplinary objects will help to increase their number in the MES creators' community (Patarakin & Vachkova, 2019).

5. Research Methods

Mining relevant data is key to building a sound recommendation system (Dwivedi & Roshni, 2017). Current research is based on data, mined from the MES repository from 2015 till 2020 (Table 1). To facilitate data processing a dedicated database was designed. The total amount of data extracted from the system exceeded 15 Gbs.

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Table 01. Number of scenarios by year

Year	Number of scenarios
2015	457
2016	8785
2017	155047
2018	650912
2019	614045
2020	229399

For each scenario the database contains the following metadata:

-title

-topic

-description

-creation date

-publication date

-copy status

-author ID

-author profile ID

-author profile type

-author's school

-discipline

-level of education

-region code

-region school

-moderation status

-study level

-number of co-authors

In addition to the scenario metadata we also used the following users' actions on the learning objects:

-copying

-adding to favorites

-launching

-viewing

The database stores additional information on the copied objects

-copied scenario ID

-ID of the user, who made the copy

-date of the copying

-copy ID

Information on rating a scenario includes:

-scenario ID

-ID of the user who rated the scenario

-date of the rating

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-the rating

For the launched scenarios the database stores the following:

-scenario ID

-ID of the user who launched the scenario

-scenario launching date

-end of launching

Table 2 contains users' actions.

Table 02. Number of scenarios by year

Action type	Number of actions
Copying	1 276 875
Adding to favorites	2 636 208
Rating	939 392
Launching	10 828 907
Viewing	15 054 814
Copying	1 276 875

For data processing, we used languages Python 3.0 and R.

6. Findings

MES learning objects repository offers teachers vast opportunities for cooperation. Its users themselves are the authors of the content as they can post on the platform materials that they develop. The system records all users' actions and this data allows us to track user's behavior patterns on the platform.

An important feature of MES repository users' behavior is their ability to build mutual relationships around creating and using learning objects of common interest. Although MES does not explicitly support tools for user interactions, like social networks or forums, relationships between them can be extracted from the data on their collective use of learning resources, as each of those interactions is recorded in the system. The process and mechanism for extracting and processing the collective usage objects were described in our previous work (Patarakin, Burov, & Yarmakhov, 2019).

The history of users' operations over the repository objects can be represented as a table, containing 17 532 496 actions, and having a similar data structure (see Table 3).

Table 3. User actions example

Scenario	User	Action	Date	School	Subject	Level
259	78069	create	2015-03-17	1194	History	General

This table can be transformed into a network graph of links between users and scenarios. For every user A, we can highlight his personal network, which includes users, who used scenarios, created by user A or created scenarios, used by user A. Such micro-network of users' relationships can be used as a profile for such users. An example of it is shown in Chart 1 (See Figure 1).

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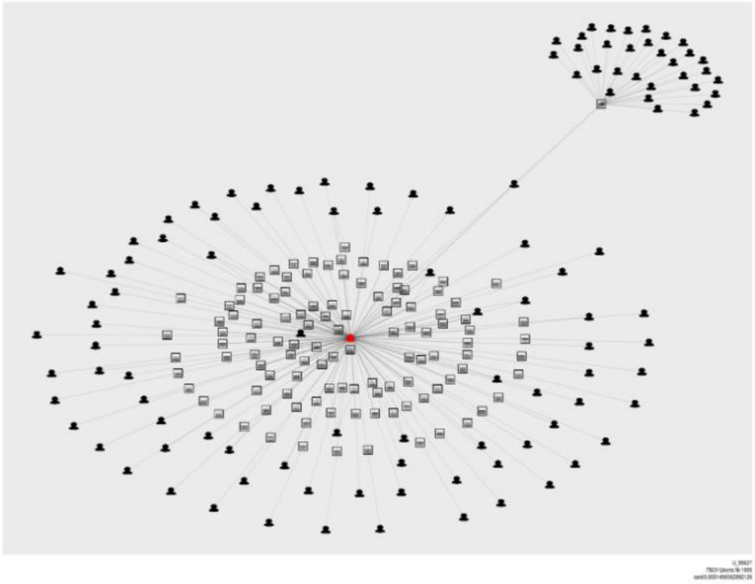

Figure 01. Learning objects repository macro and micro-networks

After we defined user interactions and relationships, we could proceed to explore the unities or clusters of MES users based on their common behaviors and choices of learning objects.

To find patterns of multidisciplinary MES repository users' behaviors we selected 7455 MES repository users who created 42442 scenarios that have successfully passed through the moderation process. Out of those users, 6219 authors created monodisciplinary scenarios, and 1236 users created multidisciplinary scenarios. All these users were clustered based on their actions on the platform which helped to define 7 clusters (see Figure 2).

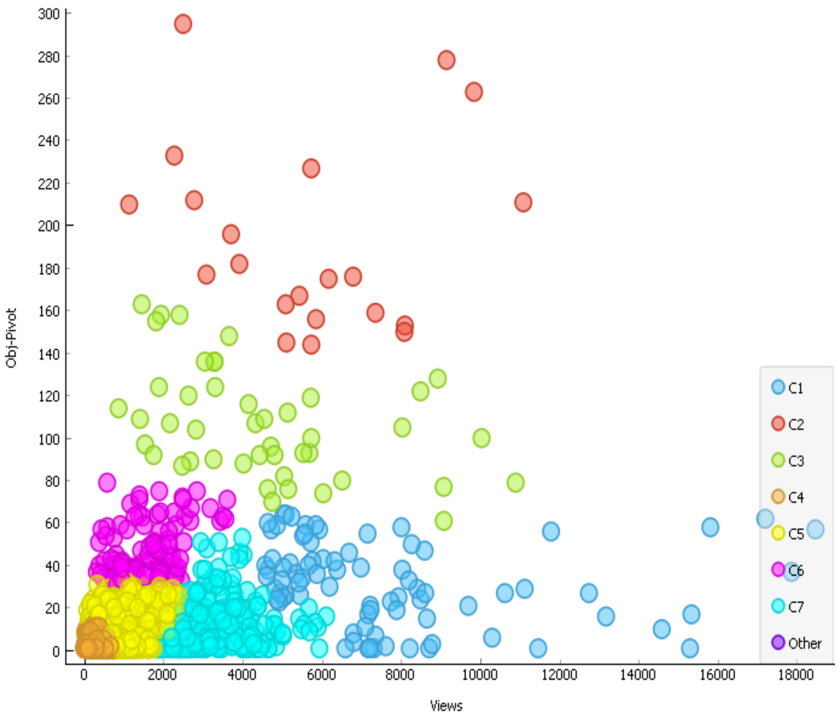

Figure 02. MES repository users' clusters

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The major cluster consisted of 5385 users who created from 1 to 3 objects and who were considered inactive in the model.

3 clusters of active users consisted of remotely active (93 instances, 37 - 59 created objects), moderately active (45 instances, 89 - 122 created objects), and significantly active (21 instances, 159 - 212 created objects).

3 clusters of lurkers consisted of remotely active (1481 instances, 840 - 1363 viewed objects) moderately active (326 instances, 2340 - 3444 viewed objects) and significantly active (81 instances, 5423 - 8492 viewed objects)

As we see, the ratio of active users to lurkers in the MES repository is 7,7%, which is very close to 1 - 9 - 90 rule, defined for active and inactive users in social networks (see Figure 3).

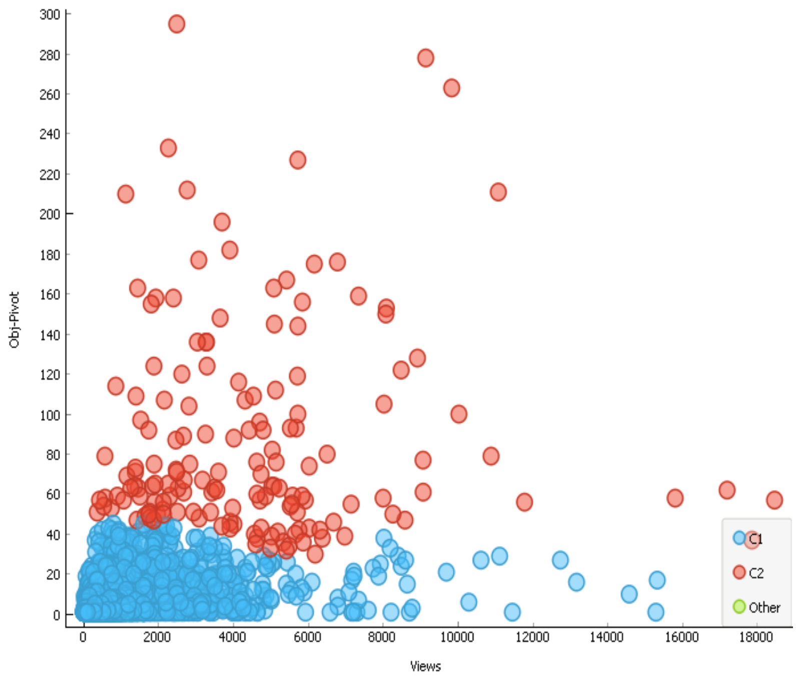

Figure 03. Active users and lurkers in MES repository

After collating the clustering data with data on mono and multidisciplinary patterns, we found out that 37% of active users created multidisciplinary scenarios, while only 17% of lurkers did so. Thus, we came to the conclusion that being active and creative in a learning objects repository, such as MES generally leads to a broad, multidisciplinary position in the repository authors' community.

As we found out, users' behavior and their ability to create new, multidisciplinary learning objects for the repository is closely connected to their network activity. The users' network parameters directly depend on their willingness to explore the other authors' content, copy and grade their learning scenarios, which leads to higher connectedness of the whole electronic learning platform domain.

7. Conclusion

Building students' multidisciplinary skills is an important task of contemporary education. These skills allow students to become better learners and make them more competitive at the job markets that they are about to enter. Still in the educational community, there is no univocal methodology of how multidisciplinary skills are supposed to be built.

The approach which we maintain in the current paper is based on the assumption that the core of multidisciplinary skills is multidisciplinary learning content, that combines concepts of various subjects and brings it to the upper level, which requires high order thinking and operation skills.

Contemporary electronic learning platforms provide vast opportunities for cooperating between teachers in creating multidisciplinary content by teams of teachers representing various school subjects. The case of Moscow Electronic School analyzed in this paper shows that the number of such subjects can reach as many as 24 for learning scenarios. An important part of promoting a multidisciplinary approach through electronic learning platforms is helping teachers to find and utilize the most applicable content of what is available on the platform, which generally falls into the domain of recommendation systems.

Constructing a successful recommendation system requires understanding relationships between the members of the educational community of the electronic learning platform. In the recommendation system context, they can be viewed as a network of nodes, each of whom builds and shares learning objects, which can be used by other nodes. Thus, in our research, we explore the connections between the members of the network and build a clustered model of it, which helps to identify groups of users with behaviors (Hoic-Bozic et al., 2016)

These observations serve as a basis for a recommendation system, which can take into consideration behavioral patterns and offer students quality learning content, focused rather on multidisciplinary than monodisciplinary skills can be very helpful as a free and open platform available for every student.

In our paper, we described a mechanism for locating authors who are likely to create such content and found that the number and quality of such authors can be increased through the delurking process. Further development of connections between users through the learning objects that they create and embed in their teaching practice will lead to a better quality of the platform resources and growth of multidisciplinary content on it. A recommendation system built on these principals can become a sound solution for changing the ratio between monodisciplinary and multidisciplinary learning objects towards the increase of the number of the latter.

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