Deliverable D.8.4. Social Data Visualization and Navigation Services

DELIVERABLE

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Deliverable D.8.4
Social Data Visualization and Navigation Services

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Abstract: Within the Open Discovery Space our study (T.8.4) focused on "Enhanced Social Data Visualization & Navigation Services. This deliverable provides the prototype report regarding the deployment of adapted visualization and navigation services to be integrated in the ODS Social Data Management Layer.

Keywords: Open Discovery Space social platform, social data management layer, social data visualization, social navigation,

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				implementation table - Update details $1-3 - $4 New update“ social recommenders ”ODS - $5 New evaluation pilot -$ 6 New Open linked data -$7 Update conclusion. - $8 updated reference list

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Executive Summary

This deliverable describes two prototypes for respectively visualization and social recommendations for implementation in the ODS learning portal. The objective of the proposed service is to support learners when exploring ODS. Data visualization and social navigation help users in ODS to find knowledgeable peers and relevant resources across the platform.

As part of the social layer in ODS intuitive services depictions and recommendations are essential to enhance online social learning interactions. The report describes the need for services and options considered and the (theoretical) considerations underlying the proposed services. Chapter 2 and 3 offer details on how to realize the ODS data visualization and recommendations. The integration of the services into the ODS platform will in the next period be taken care of in WP8 and WP9 in respectively T.8.5 and T.9.5. The 1.0v version (10/2015) of this deliverable has been updated at the end of the project period to incorporate the third year developments.

1 INTRODUCTION

This deliverable describes an architecture for the implementation of adapted visualization and navigation services in Open Discovery Space. According to the DoW, a number of portal services are expected to be deployed, which according to their technical and compliance maturity, will be made available in consecutive rounds.

It is important to remind that T8.4 is related to the deployment of front-end services for learning portals, that will provide enhanced visualization and social navigation features to ODS portal users. It will particularly embrace existing services tested in portals such as MACE[2] and Organic. Edunet[3], in order to support retrieval and recommendation of resources and learning paths based on the social activity around them and the similarities between community members. The main objective is to investigate how to combine visualization and social navigation to increase the satisfaction of users when searching for resources, to explore the use of different displays and visualizations for stimulating social interactions.

The goal of social data visualization in e-learning contexts is to create intuitive depictions of online social interactions e.g., rating, sharing, and voting about the learning objects. To increase the satisfaction of users when exploring an e-learning portal for learning resources and engage them into using the learning objects, modern e-learning technologies rely strongly on user interfaces to facilitate interactions and provide a better socialized environment for education. The interactivity between learners and the interface in an e-learning portal is considered as one of the most important aspects to improve the quality of education. To this aim, both visualization and social navigation techniques can be applied in Social Data layer management of learning portals.

In the context of the ODS project, building upon the considerations mentioned in Deliverable 8.1, the following social data are considered to be relevant for use in our ODS portal:

1. Rate
2. Tag
3. Bookmark
4. Share (FB, Twitter, email)
5. Share count (how often has an object been shared)
6. Comment
7. Joingroups
8. Posts (discussion or blog posts)
9. Following/follower

[2] http://portal.mace-project.eu/
[3] www.organic-edunet.eu

Most of this information can be easily displayed by making use of native / common modules in Drupal, the CMS of choice in the ODS portal implementation.

With respect to social data items, as defined in deliverable D8.1, there exist different visualization types and conventions that can be applied to the presentation of social data in the ODS portal. We can classify them as follows:

- Charts (Column, Line, Pie, Bar, Area, ...)
- Star graphs, sliders
- Numbers
- Tree: specially good for classification schema representation e.g., ontologies.
- Lists: a list of top-n recommended learning objects/ users
- Text, e.g., "User John Smith joined the mathematics community"
- Icons (new message, new user, etc.)
- Social graph / network: Recommendation data can be shown by using social graph/ network schemas
- Other: Avatars for people, tag cloud, benchmarks, levels, traffic lights, highlight symbol (for new or focused things), etc.

The presentation mix in ODS has and will evolve over time according to the best way to functionally optimize the representation best fitting the learning and collaboration needs of ODS users.

It is important to distinguish between **informative visualization** (output) and **interactive visualization**(as input tool for the users). Examples for informative visualization: graph, traffic lights, avatars, non-clickable thumbnails; example for interactive visualization: tree (for navigation), social graph, slider, star rating where users can also input via mouse hover (e.g. Openscout: cf. bit.ly/10nxOHN), clickable thumbnails.

The following table illustrates the social data considered in the ODS portal as it was originally designed. The rows show the webpages of ODS portal and the columns are the social data. Each cell in the following table is shown by "V" (visualization) and/or "I" (interaction). If a social data in the table has been assigned to "V", it means the related social data is visualized to the ODS user (e.g. showing the number of sharing's of a resource) and if a user wants to have a interaction with the portal (e.g. sharing a resource) its value will be "I" in the table.

Socialinfo ------- ODS Page	Tag	Rating	Sharing	Comment	Bookmark	Post	Joingroup	Follow/ connect	Recommend
Blog	V	V							-
Search		V							-
Summary	V, I	V, I	I	V, I	I	V,I			-
Group		V	V	V	V	V			-
User Dashboard				V	V	V	V	V	V,I
Discussion	V	V		V,I		V,I			-
Community	V	V				V	V		-
Event									-
Home Page	V								-

Table 1 Social data existing in the ODS Mockups

The second table below provides the update on the social data implementation in the current (09- 2015) ODS portal. The specification of ODS portal aspects have been elaborated. The symbols used to indicate V" (visualization) and/or "I" (interaction) stayed the same.

Socialinfo ------- ODS Page	**Tag**	**Rating**	**Sharing**	**Comment**	**Bookmark**	**Post**	**Join community / group**	**Add friend**	**Follow**	**Contact**	**Views**	**Activity**	**Recommend**
Home Page anonymous													V
Home Page logged in													V, I
Resources				V						I			V
Resource	V, I	V, I	I		I	I				I	V		
Summary													
Communities							I			I			V
Community	V		I				I			I			V
Community joined	V		I				I			I			V
Search resources				V									
Search communities		V											
Group search*	V, I	V											
Group create	I												
Discussion	V	V											

Socialinfo ------- ODS Page	Tag	Rating	Sharing	Comment	Bookmark	Post	Join community / group	Add friend	Follow	Contact	Views	Activity	Recommend
search*													
Discussion create *	V					I							
Discussion view*	V	V, I	I	I	I								
Blog search*	V	V											
Blog create*	I												
Blog view*[4]	V	V (I)	V	I, V	I								
Search teacher							V	V	V			V	
Search teacher, logged in							V	V, I	V, I			V	
Event													
People								I	I	I		V	
Public Profile								I	I	I		V	
Private Profile	V	V	V	V	V		V	V		I		V	
User Dashboard?													
My area													

[4] * implemented via community page.

Socialinfo ------- ODS Page	Tag	Rating	Sharing	Comment	Bookmark	Post	Join community / group	Add friend	Follow	Contact	Views	Activity	Recommend
Logged-in top menu										I, V			V

Table 2 Social data in ODS revised portal pages (September 2015).

Most of the elements of table 1 and its update to the actual situation (9/2015) in table 2 can be visualized by means of simple Drupal features. However, for ODS we need an architecture showing the visualization of a social network from the user connections' point of view. In the following sections will describe our solution and its implementation in the ODS portal.

2 SOCIAL VISUALIZATION

In this section, we will discuss the software we developed for users visualization in the ODS portal. Particularly, we applied as well as extended an open source tool, as later described, to visualize the ODS recommended users. The data we import into the application, the software configuration set by the ODS portal administrator and the output are also outlined as follows.

2.1 Method

This radial browser [1] is an open source visualization tool which illustrates simple and complex network structures in a snappy and intuitive manner. It can be used to visualize conceptual structures, social networks, or anything else that can be expressed in nodes and links. http://moritz.stefaner.eu/projects/relation-browser/relationViewer.swfThis tool displays the relations of objects, concepts and users. Users can review each node along with their detail information or click adjacent nodes to put them in the center. Figure 1 depicts a sample demonstration of the tool when applied for showing users and their relationships.

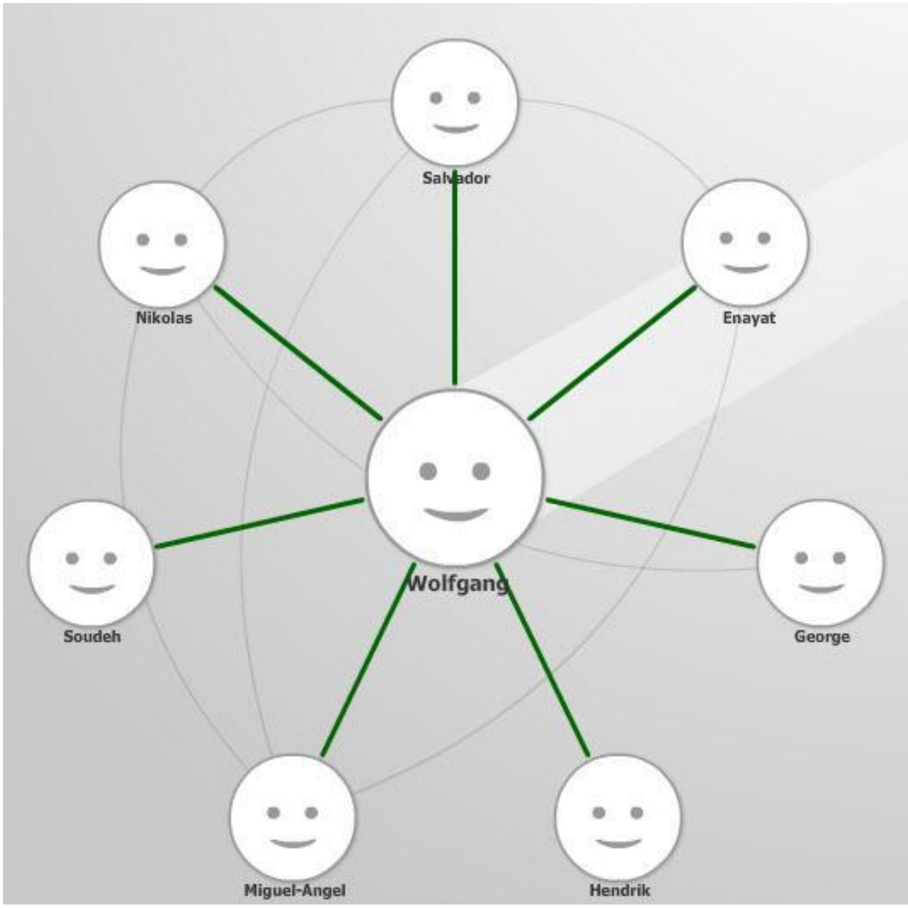


Figure 1 A sample demo of the radial browser

As a consequence of visualization we used and customized the Radial Browser interface in order to visualize the users along with their relationships in the ODS portal. Particularly the relationships between the users in this context refers to recommended ODS users to a user in the ODS portal. The following modifications have been done on the tools in order to make the interface most compatible with the ODS portal:

- Investigating how to change the source in terms of user interface and content
- Changing the graphical interface to be adaptable with the ODS visualization
- Making the starting user dynamic
- Making the information about each user customized (userID, username, type, and country)

The recommendation system in the ODS, as we will discuss later in this document, examines the users similarities and recommends a set of people to a user in the ODS social networks. The recommender' outcome is applied as an input of the visualization interface. Users along with their recommended people in the ODS network will be imported in the tool, and afterwards the software visualizes the relationship in a graph.

The following sections provide some information about integration of the implemented tool into the ODS portal. Required data as input, the configuration of the tool, and the visualization output are three important aspects of our implementation as described below.

2.2 Data

To illustrate the recommended users, we need to fetch data in two domains:

1. Recommended system output: the users identifier and their recommended users
The user' identifier (UserID) along with their recommended UserIDs will be generated by the recommended system and later stored in a relational database. The following output illustrates the results of recommended system when it is applied on sample data.

{(10,5),(10,24),(52,78),(52,86),...}

2. User profile in the ODS portal: the users information e.g., country that comes from the ODS portal
As the other user information including username, type, country, and user' image exist in the ODS portal, they are retrieved to be used in the interface.

2.3 Configuration

Radial browser visualizes the social relationships of users according to an XML file configured manually by a user or automatically by a script. The configuration file consists of the following sections:

- Setting: The settings node can have the following parameters:
    - appTitle: The title displayed in the title text field (menu clip)
    - startID: The starting point of the application (has to be a node ID)
    - defaultRadius: The standard radius for placing surrounding nodes

   - maxRadius: The maximum radius for placing surrounding nodes
- Nodes (Persons): Enumerate all node types to be used in the following parameters:
   - id: Unique identifier (userID) for the each user (case-sensitive).
   - name: The username
   - userType: The type of user (e.g., teacher, student,...)
   - country: The user country
   - imageURL: the relative URL of user image in the ODS server
- Relations (DirectedRelation): The relations of users (which user is recommended to which) with the following parameters:
   - fromID: the source userID
   - toID: the recommendeduserID

The following code depicts a sample configuration file of Radial Browser.

```
<?xml version="1.0" encoding="UTF-8"?>
<RelationViewerData>

<Settings appTitle="ODS Social Networks" WWWLinkTargetFrame="www.google.com"
startID="user_id_6" defaultRadius="170" maxRadius="240" contextRadius="230">
        <RelationTypes>
                <DirectedRelation color="0xFF2D16" lineSize="3" />
                <UndirectedRelation color="0x6633CC" lineSize="4" />
        </RelationTypes>
        <NodeTypes>
        <Person />
        </NodeTypes>
</Settings>

<Nodes>

<Person id="user_id_1" name="Wolfgang" userType="Reasearcher" country="Netherland"
imageURL="pics/wolfgang.jpg"  />
<Person id="user_id_2" name="Soudeh" userType="Student" country="Netherland"
imageURL="pics/soude.jpg"  />
<Person id="user_id_3" name="Hendrik" userType="Teacher" country="Netherland"
imageURL="pics/hendrik.jpg" />
<Person id="user_id_4" name="Salvador"  userType="Reasearcher" country="Spain"
imageURL="pics/salvador.jpg" />
<Person id="user_id_5" name="Miguel-Angel" userType="Reasearcher" country="Spain"
imageURL="pics/miguel.jpg"/>
<Person id="user_id_6" name="Enayat" userType="Student" country="Spain"
imageURL="pics/enayat.jpg"  />
<Person id="user_id_7" name="Paul" userType="Teacher" country="Germany"
imageURL="pics/paul.jpg"/>
<Person id="user_id_8" name="Nikolas" userType="Reasearcher"  country="Greece"
imageURL="pics/nikolas.jpg"/>
<Person id="user_id_9" name="Lamprini" userType="Reasearcher" country="Greece"
imageURL="pics/lamprini.jpg"  />
```

```
<Person id="user_id_10" name="Luis" userType="Student" country="Spain" imageURL="pics/luis.jpg"  />
</Nodes>

<Relations>

<DirectedRelationfromID="user_id_9" quality="100" toID="user_id_2"/>
<DirectedRelationfromID="user_id_9" quality="50" toID="user_id_3"/>
<DirectedRelationfromID="user_id_9" quality="50" toID="user_id_4"/>
<DirectedRelationfromID="user_id_9" quality="50" toID="user_id_5"/>
<DirectedRelationfromID="user_id_9" quality="50" toID="user_id_1"/>
<DirectedRelationfromID="user_id_9" quality="50" toID="user_id_7"/>
<DirectedRelationfromID="user_id_9" quality="50" toID="user_id_8"/>
<DirectedRelationfromID="user_id_9" quality="50" toID="user_id_6"/>
<DirectedRelationfromID="user_id_4" quality="50" toID="user_id_5"/>
<DirectedRelationfromID="user_id_4" quality="50" toID="user_id_6"/>
<DirectedRelationfromID="user_id_4" quality="50" toID="user_id_6"/>
<DirectedRelationfromID="user_id_8" quality="50" toID="user_id_9"/>
<DirectedRelationfromID="user_id_8" quality="50" toID="user_id_7"/>
<DirectedRelationfromID="user_id_8" quality="50" toID="user_id_1"/>
<DirectedRelationfromID="user_id_8" quality="50" toID="user_id_4"/>
<DirectedRelationfromID="user_id_8" quality="50" toID="user_id_5"/>
<DirectedRelationfromID="user_id_5" quality="50" toID="user_id_4"/>
<DirectedRelationfromID="user_id_5" quality="50" toID="user_id_6"/>
<DirectedRelationfromID="user_id_5" quality="50" toID="user_id_10"/>
<DirectedRelationfromID="user_id_2" quality="50" toID="user_id_3"/>
<DirectedRelationfromID="user_id_2" quality="50" toID="user_id_1"/>
<DirectedRelationfromID="user_id_7" quality="50" toID="user_id_8"/>
<DirectedRelationfromID="user_id_7" quality="50" toID="user_id_9"/>
<DirectedRelationfromID="user_id_7" quality="50" toID="user_id_10"/>
<DirectedRelationfromID="user_id_7" quality="50" toID="user_id_6"/>
        </Relations>
</RelationViewerData>
```

2.4 Output

Below the picture depicts the final graph when the tool[5] was applied to a sample ODS data. The output file is in Flash and can be loaded in a HTML file.

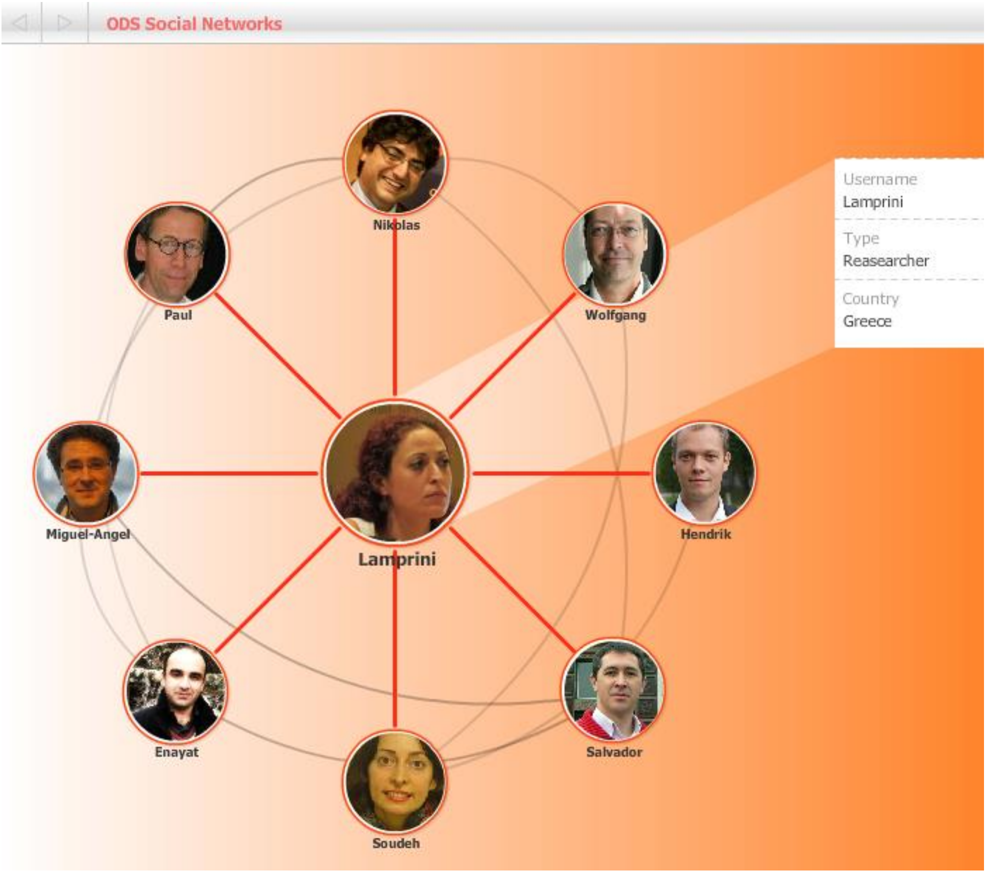


Figure 2 A social network of recommended people as shown by the radial browser using sample data

The user can also specify the core user of graph (StartID) dynamically in the HTML file used to load the Flash file. Particularly, a user can send a parameter to Flash (by making use of FlashVars) to set the identifier of user:

FlashVars="startID=user_id_9" '

To integrate the interface with the ODS portal, one script is written in order to fetch the required data (both Recommended system output and user profile) and create the configuration file in XML. From

5 http://moritz.stefaner.eu/projects/relation-browser/

the other side, if the interface is placed in each user profile, the current user ID is used to be set for the core user of the graph.

The aforementioned design considerations led in 2015 to full integration of the visualization in the ODS portal, visually presenting the user's social network as shown in the examples below. This will allow the participants not only to explore their personal network of recommended users, but also the network of other participants. In doing so, this provides the participants with a rich insight in people present in ODS as well as their expertise and involvement.

Figure 3 Social network visualization as integrated in ODS portal

3 Social Navigation

Recommendation

Earlier in our deliverable D8.2 section 3.4, we described the ODS recommender system's concept and requirements fully in details. The description elaborates on the input and output of recommendation module and the used approaches; including:

1. The types of recommendations provided and for each one:
    a. Use case reference
    b. Type of output
    c. Possible data source
2. The required CAM events
3. How to read the input data
4. How to write the output data
5. The usedrecommenderalgorithms

This description was updated many times based on several meetings between partners particularly OUNL and INTRASOFT who all finally agreed on that.

In this section, we aim to present an offline study conducted to investigate which recommender algorithm can best fit the ODS social learning platform. We needed to run such empirical study to select a proper approach in order to implement and integrate it with the ODs portal.

3.1 Goal

With the emergence of large amounts of data in various domains, recommender systems have become a practical approach to provide users with the most suitable information based on their past behavior and current context. We apply recommender systems in the context of the FP7 Open Discovery Space (ODS) project. The ODS contains large amounts of data in the field of education with a critical mass of approximately 1.550.000 eLearning resources from 75 content repositories, as well as 15 educational portals of regional, national or thematic coverage connected to it. Considering these huge amounts of data, we want to support ODS target users to find suitable content or people of their interest within ODS platform.

3.2 Method

The first step to design a recommender system for ODS is to investigate what recommender algorithm best suits the ODS target users. To do so, we need to evaluate a set of recommender algorithms on ODS dataset including user social data e.g. rating, tagging, browsing, commenting, etc. Since we have no data yet from the ODS platform and its real users, we decided to conduct an offline empirical study for testing recommender algorithms on datasets that are similar and related to the future ODS dataset. In the following sub sections, we describe the datasets and algorithms used for the offline data study.

3.2.1 Data

We selected the MACE and OpenScout datasets because of the following reasons:

1. The datasets contain social data of users such as ratings, tags, reviews, etc. on learning resources. So, their structure, content and target users are quite similar to the ODS datasets we aim to study.

2. Running recommender algorithms on these datasets enables us to conduct an offline experiment in order to study the recommender algorithm to be customized for the ODS target users before going online with the actual users of the ODS.
3. Both datasets comply with the CAM (Context Automated Metadata) format (Niemann, Scheffel, and Wolpers 2012; Schmitz et al. 2009) that provide a standard metadata specification for collecting and storing the users' data within a social online platform like the one for the ODS.

Unfortunately, the educational domain lacks a golden standard dataset to conduct data studies, such as the MovieLens dataset. Therefore, we decided to test MovieLens dataset as a reference dataset in addition to the above-mentioned educational datasets. In the rest of this section, we give an overview of the selected datasets to be studied:

1. MACE. The data was collected from MACE portal[2] that provides access to learning resources from several repositories all over Europe. It contains logged events in the time period from 01.10.2009 to 30.09.2012. The dataset contains 9,728 events conducted by 105 registered users on 5,696 learning objects. The events are included in the dataset: "addTag", "rate", "addCompetence", "getMetadataForContent", "goToPage".

2. OpenScout. The dataset originates from OpenScoutportal[3] that supports leaners and individual to search for learning objects. The dataset consists of 2,560 events conducted by 331 registered users on 1,568 learning objects. The data has been collected since end of December 2011. These are the events included in the dataset: "addTag", "rate", "viewMetadata", "goToLearningObject".

3. MovieLens. The dataset consists of rating data from the MovieLens web site[4] collected by GroupLens Research. The dataset contains 96,719 ratings from 941 users on 1,512 movies. Although it is a golden standard dataset often used for running data studies in e-commerce, it has been broadly used in other domains as well for comparison.

3.2.2 Algorithms

The educational datasets used in this study provide us with implicit indicators including browsing, tagging, commenting, etc. that represent users' interest in the respective learning objects browsed, tagged, or commented on by the users. These datasets provide too few user preference values for example in form of five-star ratings. In general, users are less likely to show their interest in an object by giving explicit ratings. Instead, we can extract their implicit interest in an object by monitoring their activities within a social online platform like the one for ODS. As mentioned before in D8.1, we refer to this data as social data of users including browsing, tagging, commenting, downloading, etc. Some of the classical CF algorithms such as Pearson correlation, or Cosine similarity are not suitable choices for this kind of data because they require explicit users' preferences for measuring similarity between users. The Tanimoto-Jaccard coefficient, Loglikelihood, and Euclidean are collaborative filtering approaches that can deal with implicit users interests in forms of the binary data (Verbert et al. 2011; Cechinel, Sicilia, Miguel-ÁngelSánchez-Alonso, and García-Barriocanal 2012). This is why, we chose Tanimoto-Jaccard, Loglikelihood, and Euclidean to be used in this data study.

Besides, we used a graph-based recommender algorithm. The graph-based approach first creates a network of users in which nodes are users and edges show similarity relationships between them. Then, it traverse the users graph to collect the recommendations for a target user (Fazeli et al.

2010). graph-based recommenders mainly aim to improve prediction accuracy of the generated recommendations even when the users data is sparse that is often the case in the educational domain (Verbert et al. 2011; Fazeli et al. 2013). Therefore, we also tested the graph-based approach on the MACE, OpenScout and MovieLens datasets.

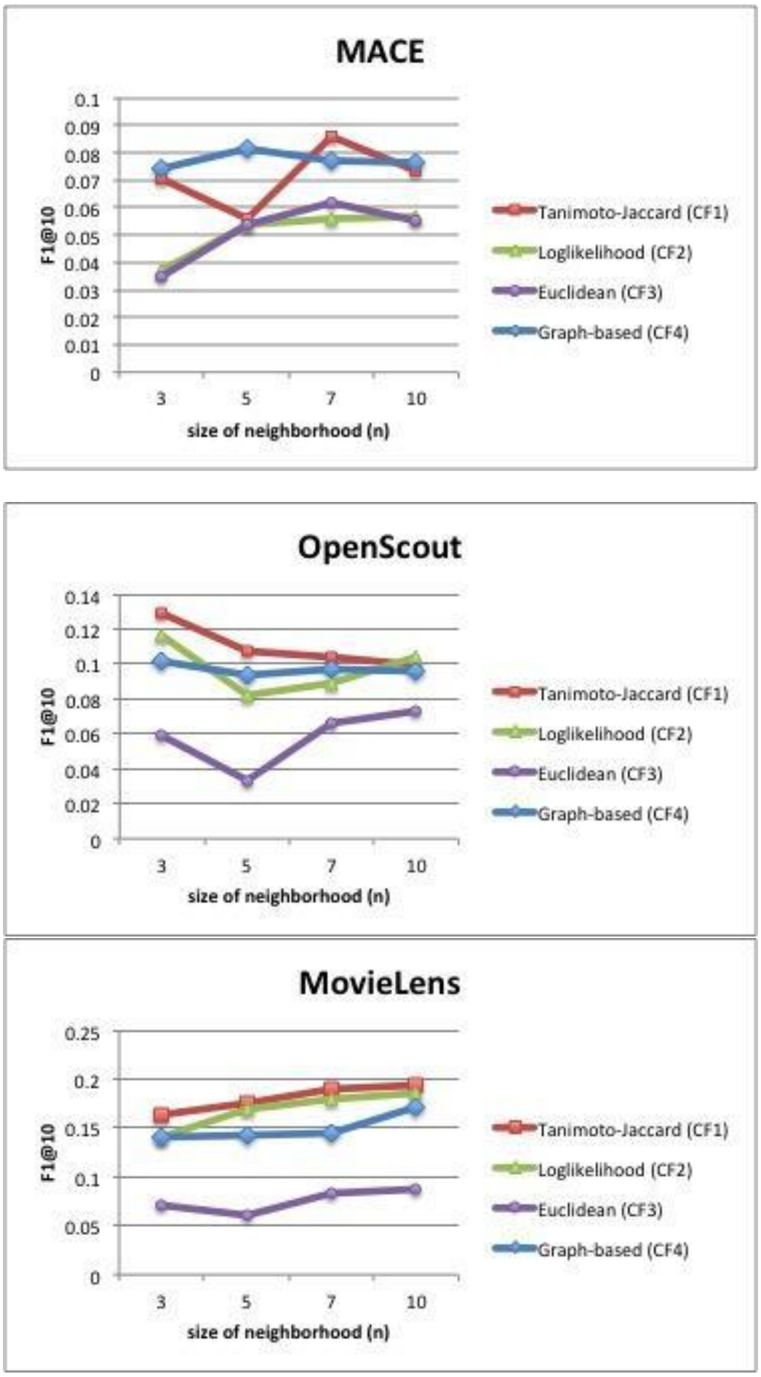


Figure 4 F1 of the recommender algorithms for different datasets, based on the size of neighbourhood

3.2.3 *Outcome*

Based on the results we have achieved so far, the graph-based approach and Tanimoto-Jaccard best perform in terms of F-measure of the generated recommendations (See Figure 3). We presented results for different sizes of neighborhoods (*n*) for collaborative filtering approaches. Based on the results, graph-based approach has a more stable behavior when *n* changes. In addition, graph-based approach provides a distributed setting that allows us to tackle scalability issues. In fact, the issue with centralized approaches such as the Tanimoto-Jaccard, Loglikelihood, etc. is that they often face scalability problems when the numbers of users or objects increases. Moreover, the classical collaborative filtering algorithms only perform well when enough ratings data are available, as it needs a user-item matrix for generating recommendations. The T-index recommender, however, generates recommendations by traversing graphs of users and works well even when the ratings data are sparse.
In addition to the performance results, we also showed that graph-based approach helps us to have a balance distribution of degree centrality that provides users with more opportunities for finding central users (See Figure 4). For the simplicity, we show degree centrality of the first 10 central users.

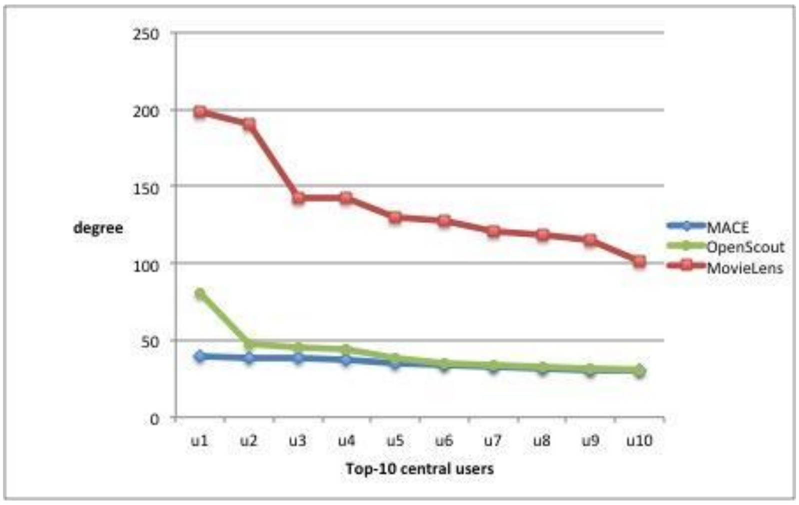


Figure 5 Degree distribution of top-10 central users for different datasets

3.3 Ongoing and further steps

We already implemented the selected graph-based algorithm and successfully tested with real-data from ODS portal. The next step was the integration with the Portal services. (WP9.5) Intrasoft would be in charge of providing interfaces to display the recommendations to the users. Since the CAM modules had not been activated for a period of time, there are still no sufficient user transactions available to create proper recommendations at the time of writing this deliverable (Dec. 2013).
Furthermore, we plan to conduct a user evaluation study when we have real users in the ODS platform. We are already exploring the planned events in the beginning of 2014 to investigate which one can best fit our user study. The user evaluation study helps us to confirm if the selected

recommender algorithm is an appropriate approach to support the real users of ODS in finding suitable content or people.

In the final year, once the platform reached is stable end of project phase, both recommender and visualization components were ultimately integrated in the ODS portal. After successful implementation we were able to execute the study with real users on which we report in paragraph 5 of this deliverable D.8.4-1.0v.

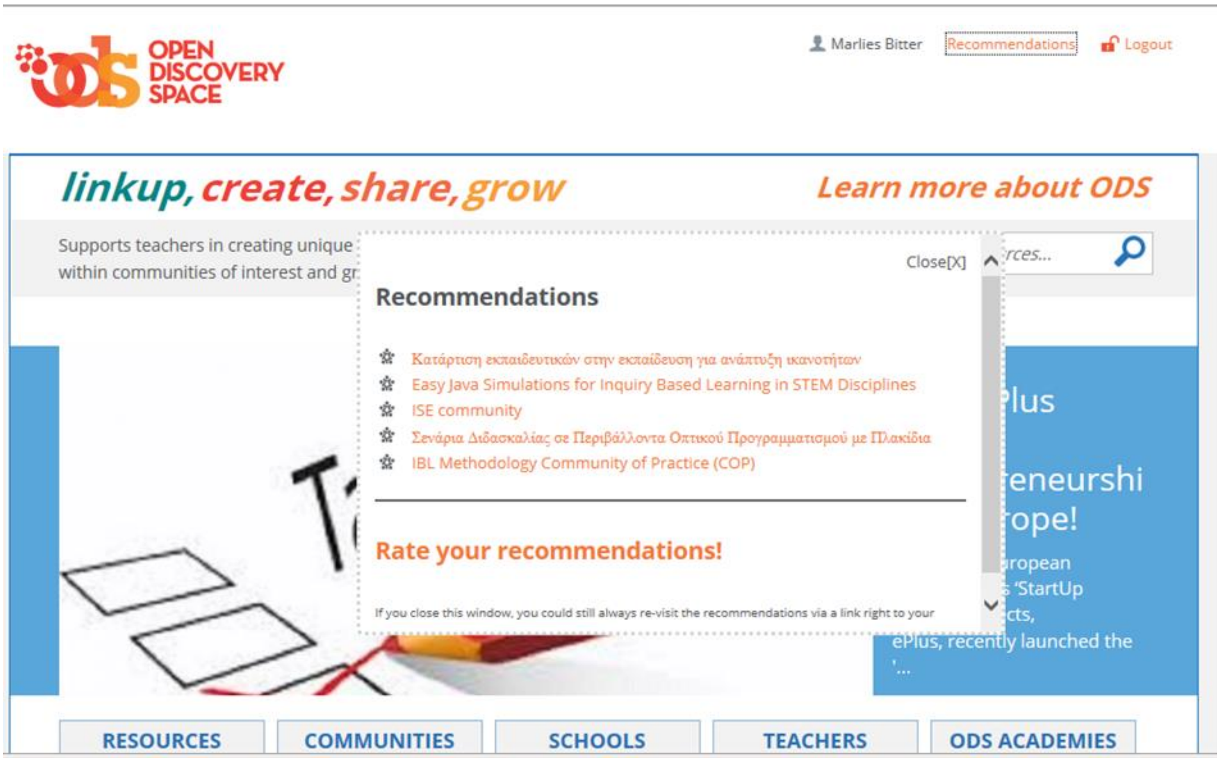


Figure 6 Implementation of personal recommendations (used for pilot study 7/2015)

3.4 Visualization

Recommendation data can be shown in all the pages that user has already logged in, (e.g. in a frame in the right side of a page) no matter what the page is about. Just please note that recommendations are made based on social actions of a user within ODS and not based on e.g. search keywords or query of a user. Besides, we currently generate only two types of recommendations: learning objects and users.
In this section we discuss the ways to show recommendations. There exists several ways to display recommendation data:

3.4.1 Lists

Lists have been used as a simple way to show recommendations. In the ODS, we can display recommended objects/ users by simple ordered lists either in a frame of the current page or as a pop-up menu.

3.4.2 Thumbnails

Another option to display recommendations is using thumbnails. They have become more and more popular as users find them more informative and interesting as well than the simple lists. For instance in Amazon, users generally are provided with their favorite products in forms of thumbnails that not only gives them information such as description of a product but also an image of the product as a brief overview.

3.4.3 Social graph/network

We can provide recommendations data in this format (user1, user2, weight) that presents a mutual relationship between two users user1 and user2 as nodes in a graph structure and the weight value can be assigned as a label for the edge between them. The output data are available in a relational database. For the moment, the recommendation data are written in MySQL database that is quite straightforward to be accessed.

4 SOCIAL DATA RELATED RECOMMENDATIONS IN THE ODS PORTAL.

In the final ODS portal version (9/2015) quite some non–personalized and personalized recommenders have been implemented. In this section we present some examples to give an indication of the type and nature of social data generated recommendations available in the ODS at the end of the formal project period.

4.1 Non-personalized recommendations: homepage

The anonymous homepage of the ODS Community portal contains many implicit, non-personalized recommendations, such as indications of:

- the upcoming event
- the number of resources, communities, schools, teachers, ODS Academies activities
- videos for ODS main, ODS for teachers, ODS for students, ODS Academies and ODS interviews
- listing the first three main news items
- listing the three upcoming events
- organizing resources, communities and people into three thematic portals: Science and Technology, World of Entrepreneurship, Geospatial thinking
- invitation to Creative Science classroom

In short, the anonymous homepage in particular puts forward interesting news and events, but also already indicates how some information and resources are organized, thereby highlighting those that are most active. These all provide implicit recommendations.

Before the UI adaptation of the ODS Community portal, the anonymous homepage indicated different format for generic recommendations like the top 10 most visited and recent visited communities news. However as recommendations are part of the overall ODS ecosystem they evolved into the current portal homepage settings where generic recommendations are presented like this.

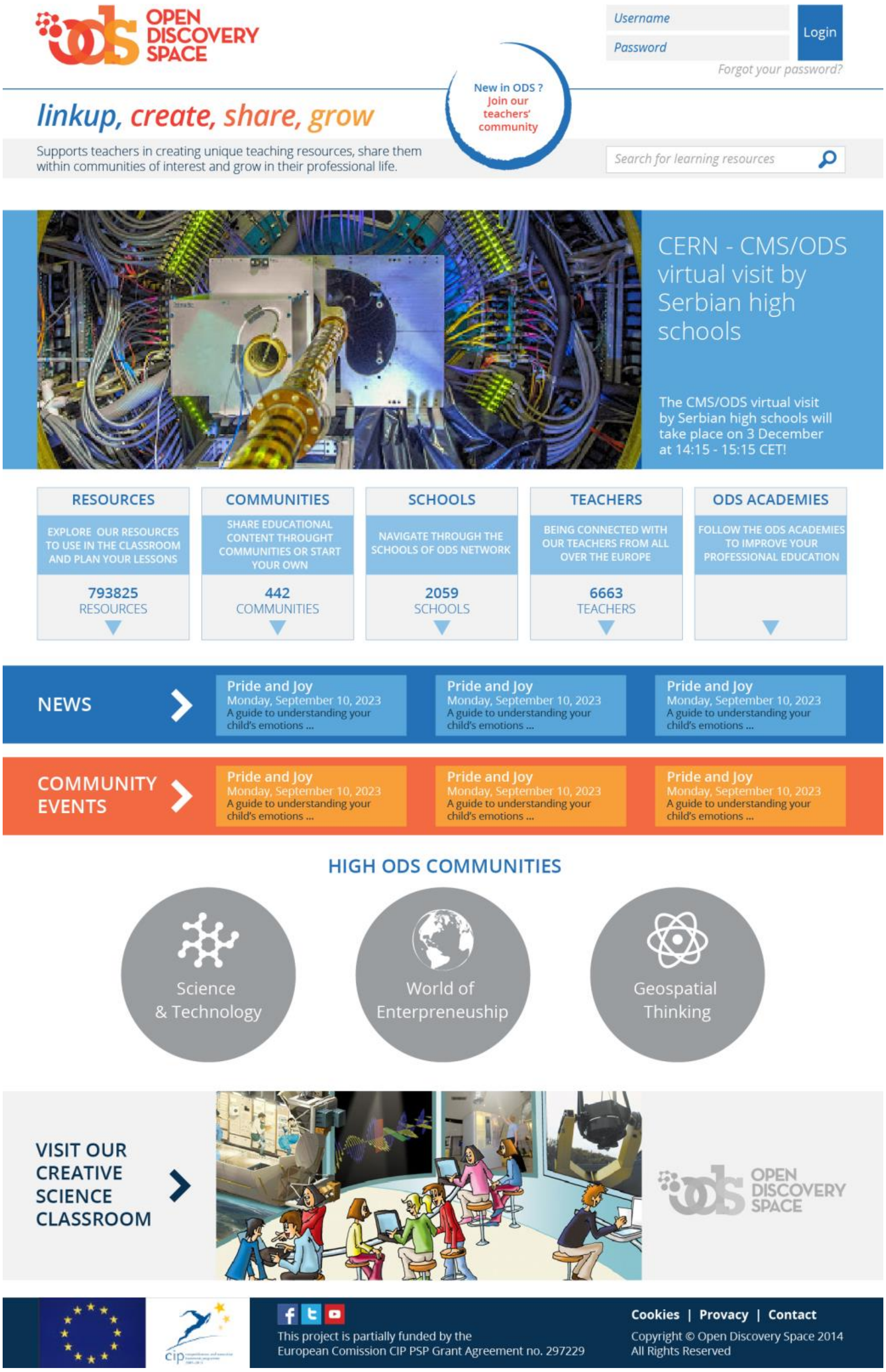


Figure 7 Homepage with non personalized suggestions/recommendations

4.2 Non-personalized recommendations: specialised pages

Resources page: The resources page also provides some implicit, non-personalized recommendations, by listing the items in a particular order, by relevance by default. One of the filters is based on user comments and provides therefore an implicit, although non-personalized, social data recommendation.

Implicit, non-personalized, recommendations are also made available by indicating the number of resources in various categories, such as discipline, language. Some of these categories are based on social data such as tags.

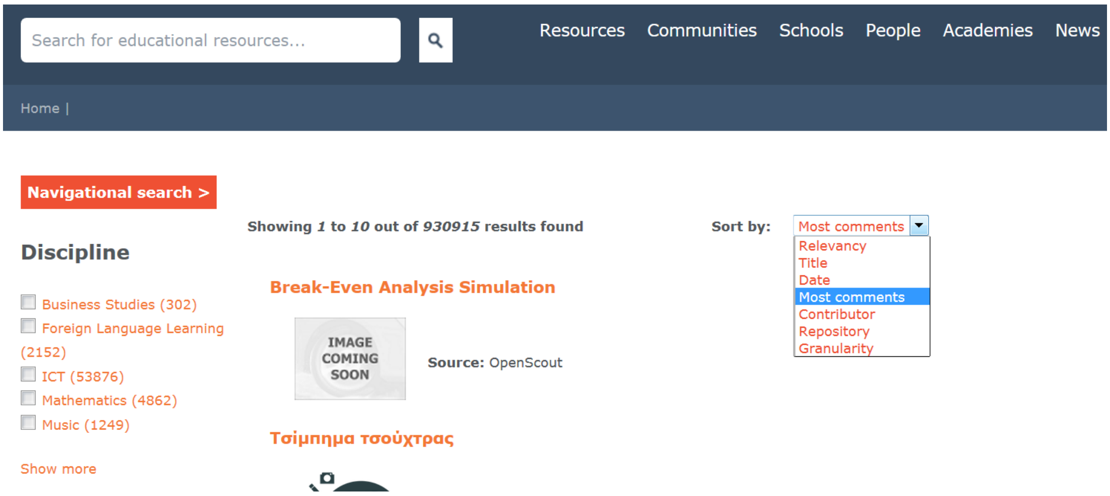


Figure 8 Implicit and non-personalised recommendation of resources based on social data

Blog and communities: search blog via community: implicit recommendations by filtering on most popular, and searching on tags

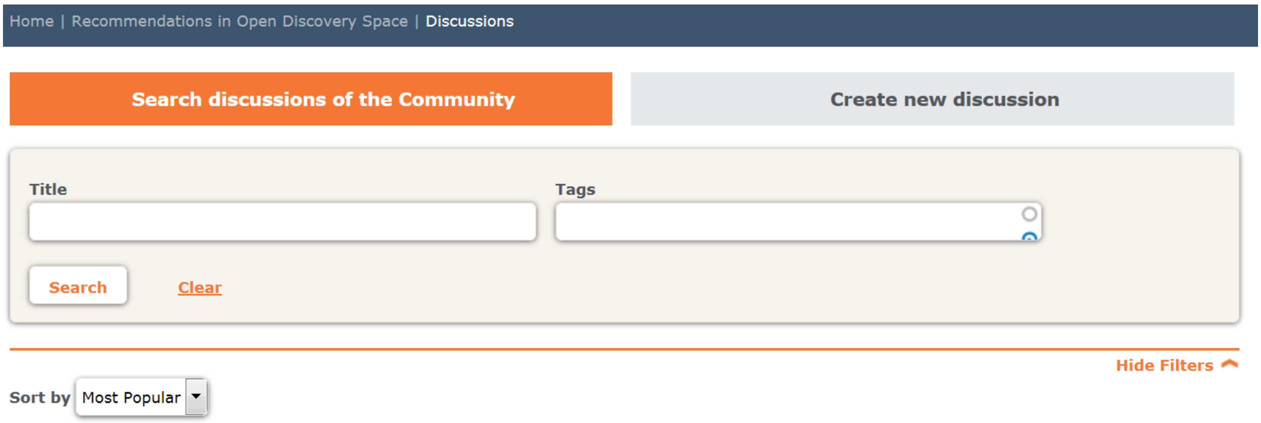


Figure 9 Filtering blogpost on social data and tags

Blogs: Blogs are part of a community. By default the blog overview is shown based on: social activity, most popular, and therefore consists of implicit, non-personalized type of recommendations. Blogs can be rated, tagged, bookmarked, and comments on blogs can be posted.

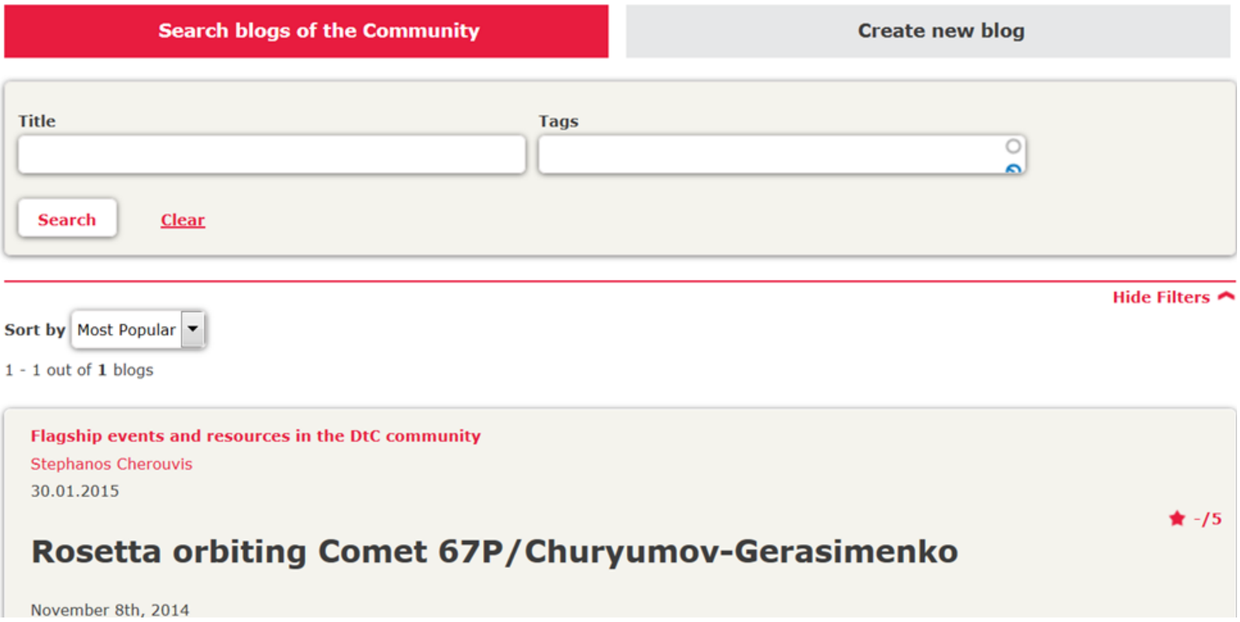


Figure 10 Blogs can be rated, tagged, bookmarked and commented

Group page via community :group pages contain implicit, non-personalised recommendations by displaying by most popular by default.

The **Network of related communities** actually is also an implicit recommendation for similar communities that share the interest of the user.

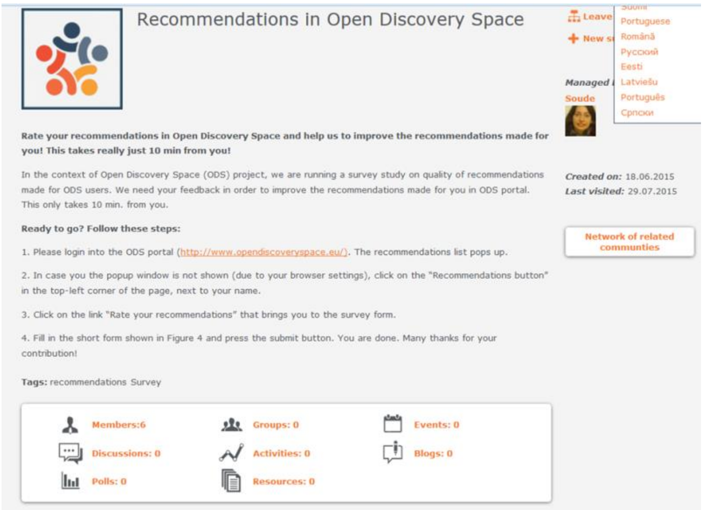


Figure 11 Network of related communities

The **Communities page** provides implicit, non-personalized recommendations based on social data by listing communities based on Most popular by default. The page also directly shows how many members the community has and allows users to directly join.

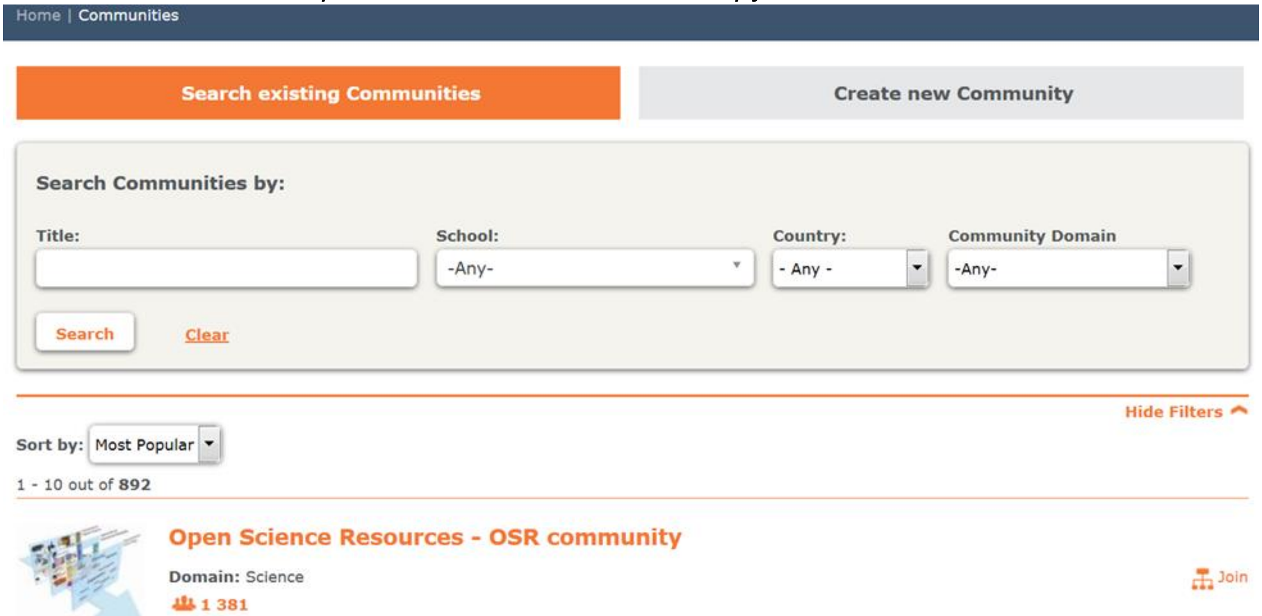


Figure 12 Implicit non-personalised recommendation of most popular recommendation and popularity

The **Community description page** indicates popularity by indicating number of members and resources

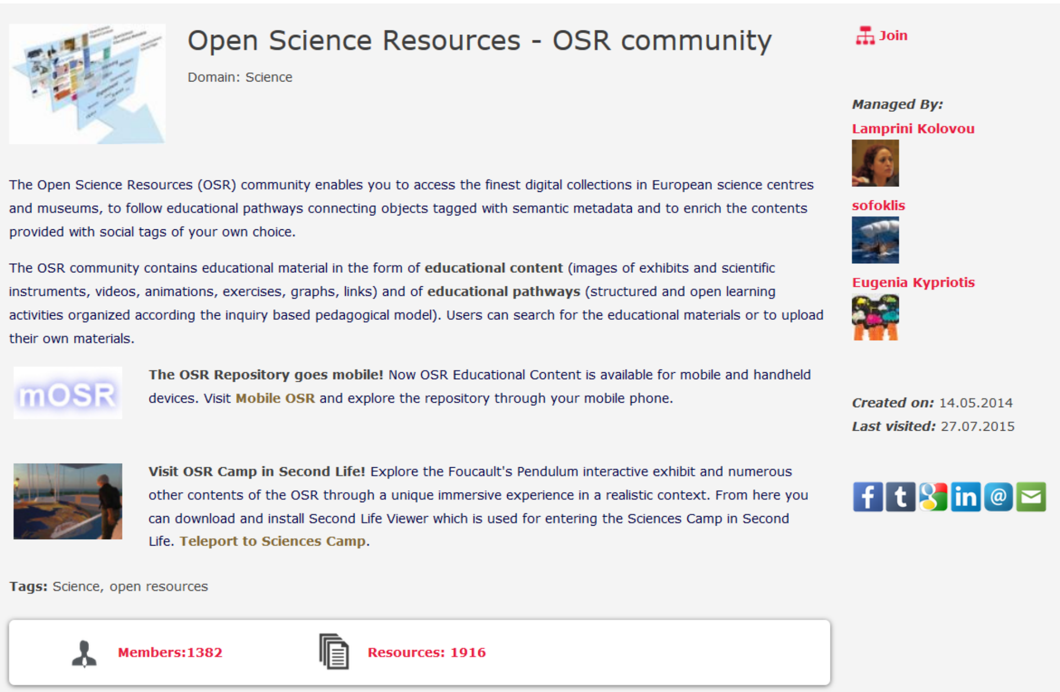


Figure 13 Social data is used to indicate popularity of communities

Finally the **joined community page**. Once joined, the number of resources, but also members can be seen as implicit recommendations that share the same interest as the user.

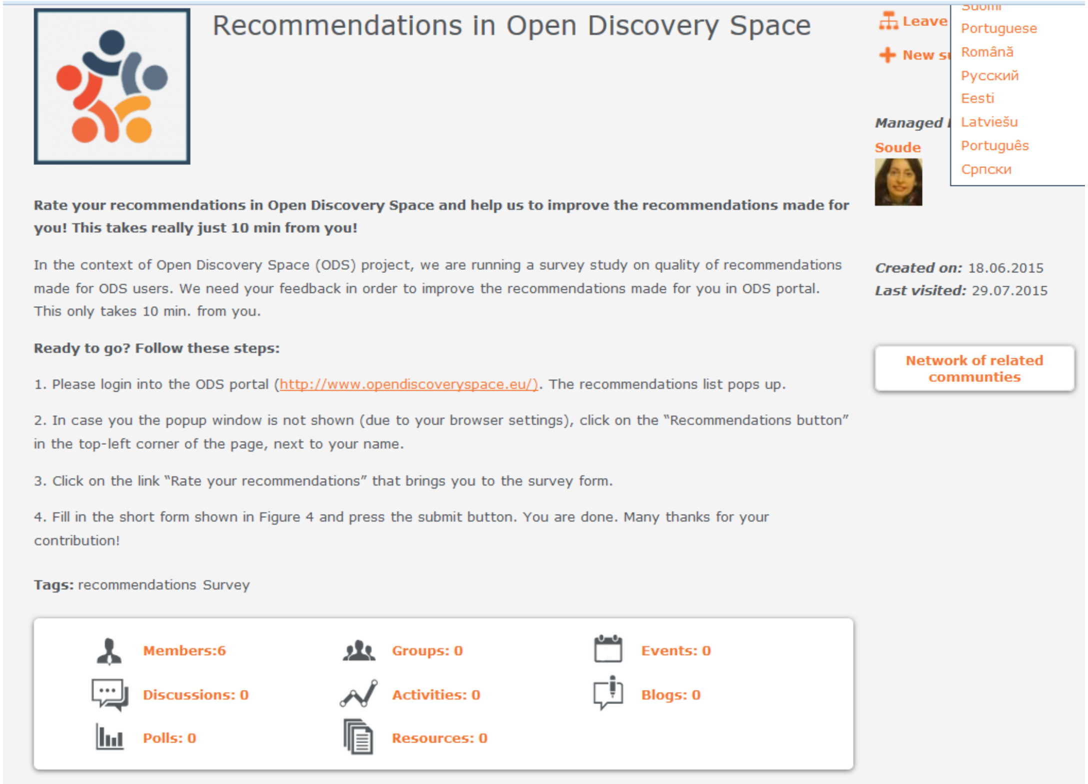


Figure 14 Social data as indication of shared interest

Profile and people pages: people pages allow users to view the profile of others, add that person as a friend to the personal network, or follow that person. The page also indicates the activity of that user, and how many points and badges that person has achieved. Social activity is displayed with relevant activity types, such as resource and blogs.

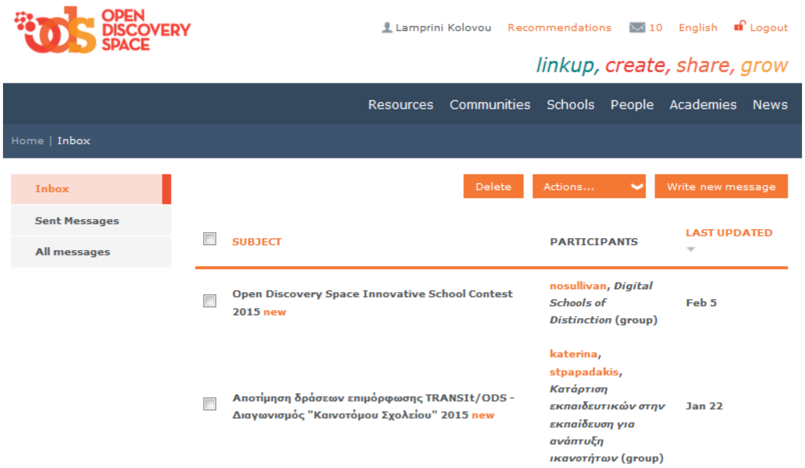


Figure 15 Interaction with other participants

Once a user has logged in, the **menu in the header** of most pages, except the homepage contains a option that allows users to contact others and obtain a list of their messages. As can be seen below

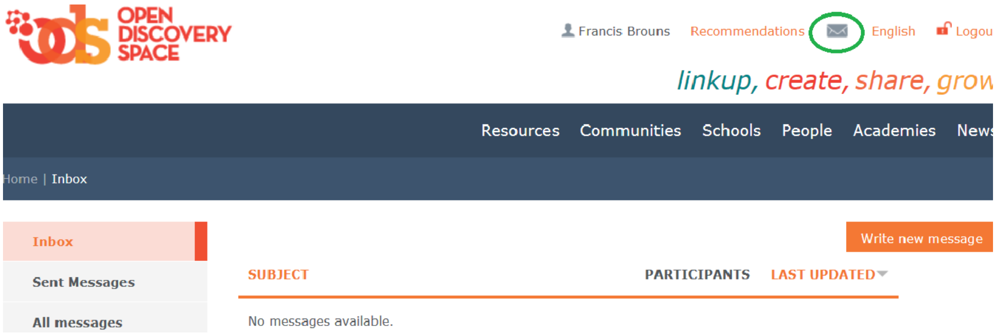


Figure 16 Easily contacting other participants

Profile page of another user: there are several, implicit, non-personalized recommendations on this page for various activity types that the user has carried out.

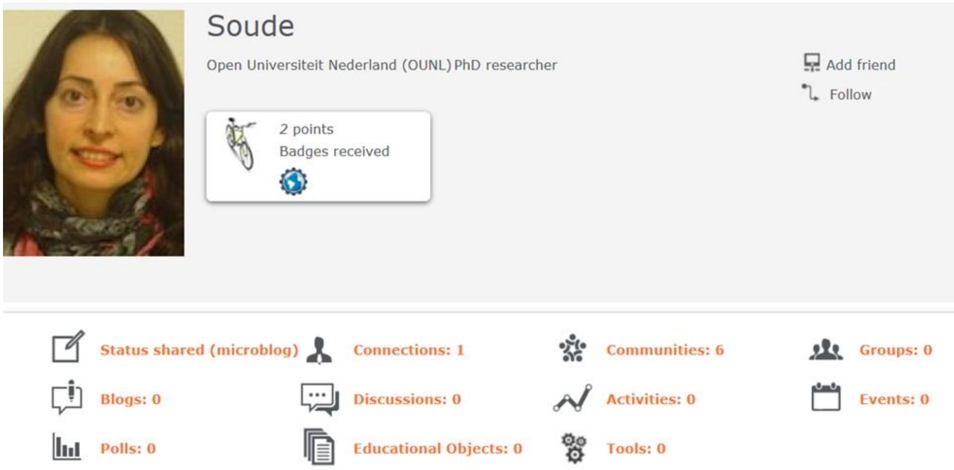


Figure 17 Implicit recommendations based on activity other participants

4.3 Personalized recommendations to logged-in users: home and profile pages

In the current version of the ODS portal once the user has logged in, the ODS Community homepage depicts the personalized item recommendations for this user, like in the examples below.

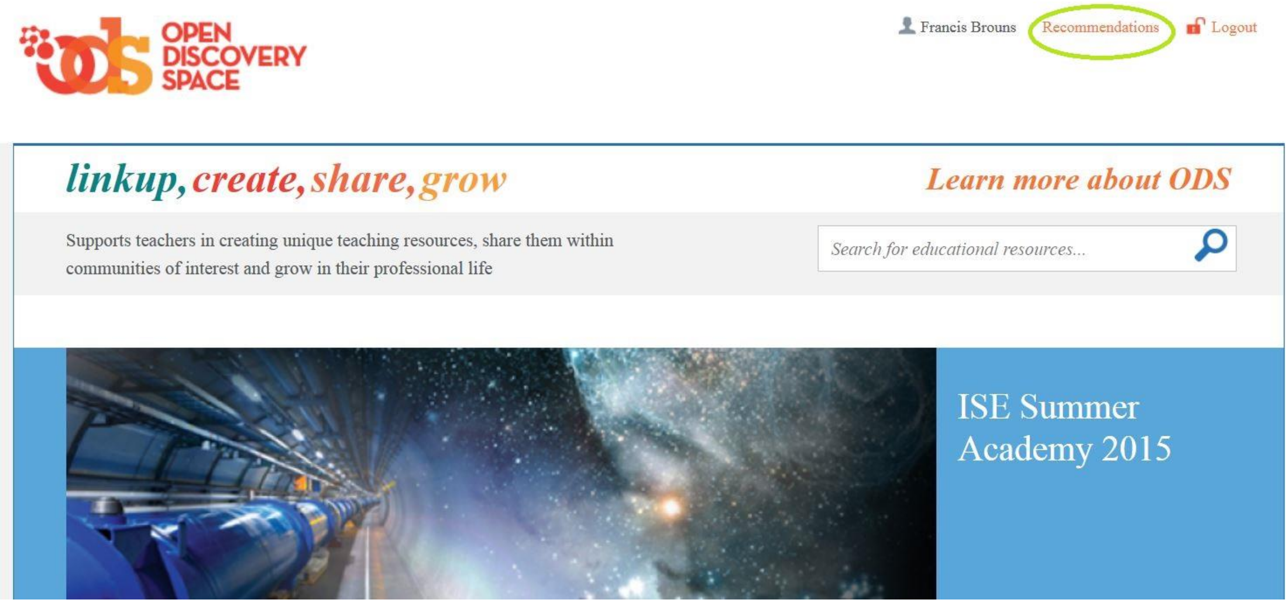


Figure 18 Accessing personalised resource recommendations

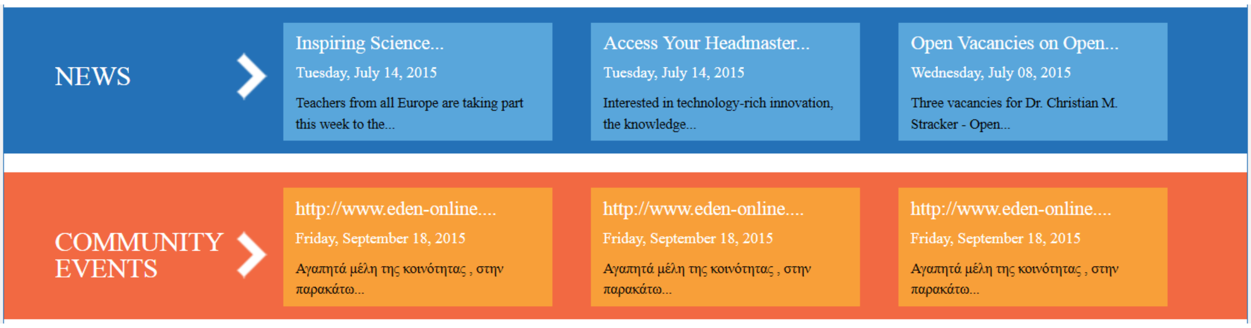


Figure 19 Homepage personalized after log-in

Then pop-up recommendations are offered to recommend the specific user (Bitter) relevant resources based on the persons social interactions across the ODS portal and its communities.

- Κατάρτιση εκπαιδευτικών στην εκπαίδευση για ανάπτυξη ικανοτήτων
- Easy Java Simulations for Inquiry Based Learning in STEM Disciplines
- ISE community
- Σενάρια Διδασκαλίας σε Περιβάλλοντα Οπτικού Προγραμματισμού με Πλακίδια
- IBL Methodology Community of Practice (COP)

Figure 20 Personal recommendations generated for a specific user

These recommendations differ for each user, based on the actions taken and tracked. E.g. the following user (lkolovou) has another list presented under the option of "Recommendations" as listed in the image below.

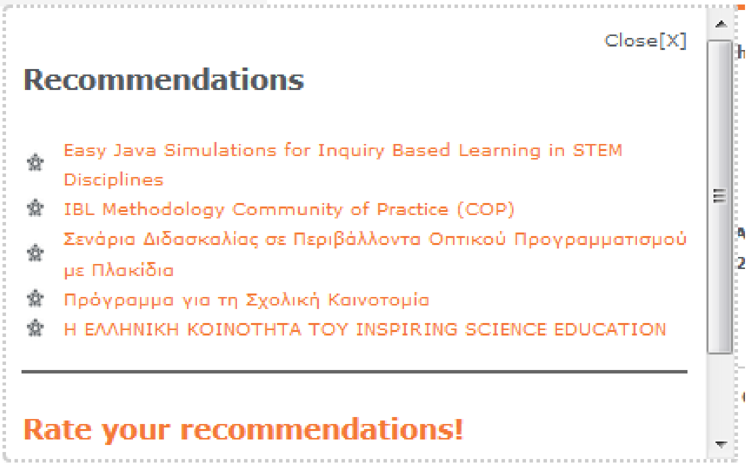


Figure 21 Personal recommendations differ for every user

Competence profiling for recommendations: Competence Profile D4.1 describes how teachers are assisted in finding the most relevant education resources based on their characteristics and competence level, are advised about and presented with a suitable template lesson plan through a matching algorithm. That algorithm is used to adapt search results. Aside to that in the future the competence profile can also be used for further refinements of the recommendations.

5 EVALUATION STUDY OF PERSONALIZED RECOMMENDATIONS IN ODS

Via a recommender evaluation study we wanted to investigate which of the recommender algorithm best fits the social learning platforms of Open Discovery Space (ODS). The ODS portal combines elements of traditional learning management systems with those of social networks. We therefore utilize social interactions of users (rating, tagging, commenting, etc.) to make recommendations on learning resources (cf. Dron & Anderson, 2014). Prior to the final evluation study we made use of graph-walking methods to improve performance of the well-known but ill-suited baseline algorithms. In this ODS study, to explore which recommender approach best meets expectations of the ODS users in ODS portal. This was an important step to finally select the most suitable recommender algorithms for implementation in the project's final version of the ODS platform. However, selecting a suitable recommender approach only based on such metrics and evaluation might not suffice as real users might have different opinions (Pu,et al, 2011, Knijnenburg, et al 2011). Therefore we wanted and managed to conduct a user evaluation at the ODS Attica Summerschool July 2015 to measure user satisfaction of personalized recommendations generated in the current ODS platform.

5.1 Method of pilot evaluation

For this evaluation, we followed the method proposed by Manouselis et al. to evaluate Technology Enhanced Learning (TEL) recommender systems (Manouselis,et al, 2012). After development of the conceptual model based on a literature review and,and an interview study (Fazelli et al ,2014), we conducted an offline data experiment to investigate if and how use of graph-walking recommenders can help to improve prediction accuracy of the recommendations made, based on data collected from social learning platforms similar to the one for ODS. The results have been reported in the ODS deliverable D8.4 (version 1.0) and also in the article (Fazeli, et al 2010). As a complementary step, we wanted to run a user evaluation to measure user satisfaction on the recommendations generated within the ODS platform using the candidate recommender algorithms: the graph-based approach proposed in ((Fazeli, et al 2010), the k-Nearest Neighbors (kNN) method, and the Matrix Factorization (MF) method. In this user evaluation, we focus on five quality metrics of the recommendations, which are proposed in the recommender systems literature (Pu,et al, 2011, Knijnenburg, et al 2011). : 1- Accuracy, 2- Novelty, 3- Diversity, 4- Usefullness, and 5. Serendipity.
First we ran the online survey from May-August 2015. In total, we received feedback from 50 participants. We disseminated the call for participation through several communication channels including ODS Facebook page, ODS events, workshops, and conferences held during the user evaluation period. Next we also took advantage of the ODS Academy school July 12-17, 2015 in Greece, Mati in order to get more feedback from the ODS users .The participants were teachers, school leaders, educational advisor, and experts from both primary and secondary school. They were both female and male (almost half-half) from these European countries: Austria, Bulgaria, Croatia, Cyprus, Estonia, Finland, France, Germany, Greece, Ireland, Lithuania, the Netherlands, Poland, Portugal, Romania, Serbia, the UK.
Next we present the user evaluation design and the questionnaire,before summarizing prelimary results.

5.2 Evaluation study design & questionnaire.

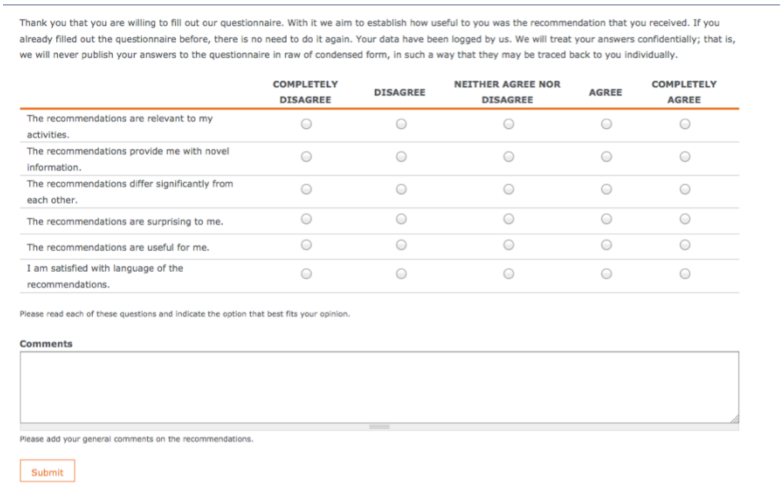
We had a set of candidate recommender systems R1. Rn where n is number of candidate recommender algorithms. We ran the recommenders on the data coming from user activities within the ODS platform. Based on the results of such data evaluation, we choose the three best-performing recommender approaches for the user evaluation (R1, R2, R3). Thus, we generated online recommendations for all ODS users and then, made the recommendations available in the ODS platform. A user sees her/his recommendations made either by R1, R2, or R3 once logging both in the home page and in her/his dashboard. They can choose whether they want to participate in the survey (user) evaluation or not by clicking on a link. We added a link right below the recommendations under the title “Rate your recommendations”. This link brought users to the questionnaire where they could express their feedback on their recommendations. This means that there may be confounding sequence effects, since participants enter in the experiment one after the other. To avoid sequence effects, treatments (types of recommendations) should be assigned in random order over time. Since it is technically not feasible to administer a randomly drawn treatment per user recommendation event, treatments are administered in blocks (randomized block design). For instance R1-R2-R3, then R3-R1-R2, then R2-R1-R3, where the numbers refers to types of recommender algorithms. If there is a sequential effect, it will be balanced out over time indeed. To make sure that any user fills out the questionnaire once only, the users are blocked from viewing the questionnaire a second time.

Finally, we asked all users a few questions on how helpful the recommendations were to them. Figure 1 shows the questionnaire we used for this online user evaluation. The questionnaire contains six statements: five questions regarding quality of the recommendations and one regarding the language of the recommendations. In addition to these six statements, we added one open question where the users can provide their general comments.

The statements were:

1. The recommendations are relevant to my activities (Accuracy).
2. The recommendations provide me with novel information (Novelty).
3. The recommendations differ significantly from each other (Diversity).
4. The recommendations are useful for me (Usefulness).
5. The recommendations are surprising to me (Serendipity).
6. I am satisfied with the language of the recommendations.

The answers on a Likert scale ranged from “completely disagree” (1) to “completely agree” (5).



Thank you that you are willing to fill out our questionnaire. With it we aim to establish how useful to you was the recommendation that you received. If you already filled out the questionnaire before, there is no need to do it again. Your data have been logged by us. We will treat your answers confidentially; that is, we will never publish your answers to the questionnaire in raw of condensed form, in such a way that they may be traced back to you individually.

	COMPLETELY DISAGREE	DISAGREE	NEITHER AGREE NOR DISAGREE	AGREE	COMPLETELY AGREE
The recommendations are relevant to my activities.	○	○	○	○	○
The recommendations provide me with novel information.	○	○	○	○	○
The recommendations differ significantly from each other.	○	○	○	○	○
The recommendations are surprising to me.	○	○	○	○	○
The recommendations are useful for me.	○	○	○	○	○
I am satisfied with language of the recommendations.	○	○	○	○	○

Please read each of these questions and indicate the option that best fits your opinion.

Comments

Please add your general comments on the recommendations.

Submit

Figure 22 Questionnaire Recommender Evaluation study

5.3 Preliminary results

The results show that most of the participants agreed on usefulness of the recommendations regardless of type of the recommender algorithms.
Find below some interesting comments from the participants:

"It is great to have recommendations sent to me, tailored to my needs. I would not have the time to go through all the communities and their activities and thanks to the recommendations; I am a 3 or 4 click away from useful information…"– A school leader and educational advisor from a secondary school in the UK

"…one of the recommendations was extremely interesting to me, and I'm not sure I would have found this community on my own. The other ones were only somewhat intriguing, but not irrelevant. However, I think I could have found these resources without the aid of a recommendation. That said, the one surprising and novel recommendation really won me over: this recommendation was impressive! An added benefit of the recommendations, in general, is that they provided me with an added incentive to further explore and consider topics, communities, and materials." – A secondary school teacher and educational expert from the Netherlands

Based on the average rating scores on all quality metrics (five metrics mentioned above) except than diversity, the graph-based recommender stands in the first place but very closely to the other two: the kNN and the MF. For diversity, the MF achieved the highest score but still very close to the ones for the graph-based and the kNN. All the algorithms got average ratings above 4 (out of 5) for four of the quality metrics: 1. Accuracy, 2. Novelty, 3. Diversity, and 4. Usefulness. The case for the fifth metric, Serendipity, was different. The algorithms received rather low scores (3.5 in average), which was expected due to the complexity of this feature from a psychological perspective. The term "serendipity" is rather tricky to be interpreted and thus, it is rather complicated to reflect on it. Therefore, the result for Serendipity metric was quite expected. The results of the user evaluation with the actual charts, percentages and numbers will be published in an article of the ODS project.

5.4 Preliminary conclusions

After running an offline experiment on the data for ODS we further investigated whether the actual users of ODS platform are also satisfied with the recommendations made for them. Therefore, we conducted an online user evaluation regarding the recommendations made for the users within the ODS platform. Based on the results, the participants appreciated the idea of receiving recommendations since they already felt being overloaded by too much content like many resources, communities, groups, etc. in the ODS platform. The results show that the graph-based recommender got higher scores compared to both the nearest neighbors and matrix factorization methods. For the live system of ODS, we therefore implemented the graph-based recommender engine. The graph-based recommender has been already customized for ODS data and integrated to the ODS platform.

6 ODS SOCIAL DATA SERVICES AS LINKED SOCIAL LEARNING DATA INFRASTRUCTURE

In task T.8.5 we focused in the final year on the pilot deployment of the Social Data Management Layer and of its services as a Linked Social Learning Data Infrastructure. One that can scale up to cope with the massive volume and heavy computational needs that the accumulation of social and usage data throughout the evolution and growth of Open Discovery Space will eventually bring.

The nature of social and usage data is streamed. This means that their creation rate is very high when Open Discovery Space usage grows. This fact implies that the infrastructure and the various algorithms (recommendations,visualizations etc) used should support the possibility of Open Discovery Space high growth and evolution.

From a (WP8.5) infrastructure perspective this is tackled by installing the whole social data layer to the GRNET Cloud. So when more resources(hard disk space, ram, cpu etc) are needed the administrator of the hosting cloud can configure it to support the new increased needs without any implication to the stability of the social data layer.

The current number of social activities of portal users over the eLearning resources in the ODS portal is not yet significant. With 521 records with rating, 1,925 records with sharing, 43 records with comments, 1,139 records with tags at the time of writing (9/2015) the current e-infrastructure is not stretched enough in order to estimate an upper reliability threshold.

7 CONCLUSIONS

For ODS deployment of front-end services in learning portals, we need to provide its users with visualization and social navigation features to facilitate their learning. In this report we focused on design and implementation efforts concerning the developed visualization and social navigation services.

To visualize the recommended (peer) users to an ODS user, we presented the Radial Browser (an open source tool) developed and implemented for integration in the ODS Portal. The tool illustrates a collection of users who have relationship to each other in the form of vertices and edges in a graph. In the current proposition user profile data (i.e. Username, user type) along with their relationships which are the recommended users' information are imported as well as integrated in the tool so that a social visualization graph emerges. Based on the documentation in this deliverable, the explanation of the tool, its implementation, plus the technical configuration for ODS portal integration, we look forward to the actual integration into the ODS platform and investigate then the effect of a radial browser visualization embedded in the combined ODS support services and see how it facilitates learning interactions of ODS users.

The selected graph-based algorithm has been successfully tested with data from the ODS portal. Intrasoft is in charge to realize that the interfaces display these recommendations to ODS users.
It is our intention to run a user evaluation study to customize and adapt the presented recommender module to let it meet more effectively the ODS user's needs and expectations. From the design and prototyping work done (in T.8.4.) the work in the coming period (i.e. T.9.5) is on the realization of the integration of the aforementioned visualization and recommender services into the social layer of ODS, scale it up and pilot test it.

At the midterm review WP8 deliverables were approved. The reviewers' comments then noted that at that time the proposed recommender and visualization services were not yet implemented. Logically since the pilot implementation of the social data layer as Linked Social Learning Data Infrastructure, had only started (according to plan) at that time (by M22).
Hence we focused in the final year on implementation of the social data layer as Linked Social Learning Data Infrastructure and the full integration of recommender and visualization services into the final version of the ODS portal.

Concurrently we worked on pilot deployment of the Social Data Management Layer and of its services as a Linked Social Learning Data Infrastructure and on the complete integration of the final design of the social data based recommender and visualization services.

After completion of the integration of these services into the ODS portal, a complex and at the same time fully operational system in evolution, we were glad to notice that first explorations of non-personal and personal recommendation services implemented, point to positive user perceptions and perceived added value.

Further work is needed into various aspects of the social recommender services and linked open social data. Varying from further improvement and dedication of the implementation to further investigation, aimed at acquiring in depth knowledge on the mechanisms of these services, once embedded into evolving social learning environments. Looking at for example the intensity of recommender use over time. Or studying effects of recommendation use on social learning processes in various communities and effects on creating new connections or strengthening existing connections in the ODS network.

Currently the outcomes of the recent evaluation studies report that especially in ODS-type of environments recommender and visualization services offered are perceived as very useful in an environment where one easily feels overloaded by the richness of resources and opportunities that the platform offers.

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