Computers & Education 118 (2018) 166–181

Contents lists available at ScienceDirect

Computers & Education

journal homepage: www.elsevier.com/locate/compedu

Social tagging strategy for enhancing e-learning experience

Aleksandra Klašnja-Milićević[a], Boban Vesin[b,*], Mirjana Ivanović[a]

[a] Faculty of Sciences, Department of Mathematics and Informatics, Trg Dositeja Obradovića 3, University of Novi Sad, Serbia
[b] Norwegian University of Science and Technology, Department of Computer Science, Sem Sælandsvei 9, Trondheim, Norway

A R T I C L E I N F O

Keywords:
Architectures for educational technology system
Human-computer interface
Intelligent tutoring systems
Programming and programming languages
Teaching/learning strategies

A B S T R A C T

Success of e-learning systems depends on their capability to automatically retrieve and recommend relevant learning content according to the preferences of a specific learner. Learning experience and dynamic choice of educational material that is presented to learners can be enhanced using different recommendation techniques. As popularity of collaborative tagging systems grows, users' tags could provide useful information to improve recommender system algorithms in e-learning environments. In this paper, we present an approach for implementation of collaborative tagging techniques into online tutoring system. The implemented approach combines social tagging and sequential patterns mining for generating recommendations of learning resources to learners. Several experiments were carried out in order to verify usability of the proposed hybrid method within e-learning environment and analyze selected social tagging techniques.

1. Introduction

Contemporary adaptive and intelligent web-based educational systems are designed to make various learning content and services available to learners. Learning content can vary from non-interactive course material, simple quizzes and exercises to highly interactive personalized or collaborative lectures (Wu et al., 2012). In order to make learning process more efficient for different learners, an e-learning system should motivate learners and offer educational material in the most appropriate form and in the most effective way (Tang & McCalla, 2005). Learners have various individual needs and characteristics such as different prior knowledge, cognitive abilities, learning styles, motivation, etc. Hence, they cannot be treated in a uniform way.

The adaptation of learning content and the personalisation according to performance and progress of a learner is significant concern for learning process. Personalized recommendation approaches are first proposed in e-commerce area for product purchase (Balabanović & Shoham, 1997; Resnick & Varian, 1997), where they helped consumers find products they would like to purchase by creating a list of recommended products for each given consumer (Cheung, Kwok, Law, & Tsui, 2003; Schafer, Konstan, & Riedl, 2001). Recommender systems (RS) could be used in e-learning environments to help learners perform relevant learning actions that suit their needs and their personal profile.

According to these learners' activities and communication between learners, we proposed a hybrid method that will extend possibilities of traditional recommendation methods within e-learning systems and environments. The proposed method combines collaborative tagging techniques with mining sequential patterns to recommend optimal navigation through the learning material to a specific learner.

The proposed method includes use of tags entered by students, ranking of the tags' influence on the learning process and subsequent use of these rankings in determining and recommending personalized paths through learning material to learners. First, the

* Corresponding author.
E-mail addresses: akm@dmi.uns.ac.rs (A. Klašnja-Milićević), boban.vesin@ntnu.no (B. Vesin), mira@dmi.uns.ac.rs (M. Ivanović).

https://doi.org/10.1016/j.compedu.2017.12.002
Received 7 May 2017; Received in revised form 1 November 2017; Accepted 5 December 2017
Available online 08 December 2017
0360-1315/

system collects the tags from learners that represent their insights and opinions about visited educational resources. In the following stage, collected tags are evaluated and ranked based on their influence on the teaching process. In the final stage, calculated ranks of the tags are used to recommend sequence of learning resources that the learner should visit next.

In order to evaluate and assess our approach, we performed the analysis in three steps:

1. Precision/recall metrics have been used to determine the most suitable recommendation method among those identified as possible and well-proven in e-commerce.
2. Implementation of a module in programming tutoring system to support the proposed hybrid method.
3. Analysis of learners' satisfaction with the programming tutoring system with tagging options.

The goal of this paper is to evaluate the usability of proposed hybrid method, by its implementation in an existing tutoring system for teaching Java programming basics. The experiments were performed to determine the most efficient recommendation method and identify the level of learners' satisfaction with the e-learning system enhanced with the proposed hybrid method.

The rest of this paper is organized as follows. In Section 2, we summarize recent research on use and effects of collaborative tagging for knowledge building and learning. This section also contains a brief overview of the research and evaluations performed on implementation of different recommendation techniques in the programming tutoring system, which was also used for implementation of the hybrid method. Section 3 presents theoretical background of collaborative tagging and mining sequential patterns. Section 4 explains the proposed hybrid method that combines social tagging with mining sequential patterns to generate recommendations of learning resources to learners. An application of the defined model in programming tutoring system is presented in Section 5. The following section contains details about the performed metrics used to determine the most suitable recommendation method and the analysis of the users' satisfaction with the enhanced programming tutoring system. Finally, Section 7 provides concluding remarks and outlines future work.

2. Background information

In this section we summarize recent research on use and effects of collaborative tagging for knowledge building and learning, as well as brief overview of research and evaluations performed on the implementation of different recommendation techniques in the programming tutoring system. The versions of the ProTuS system, the novelties and the features introduced with each of them, have been explained in the subsection 2.2 of this new section. The subsection 2.2, named "Existing work with ProTuS", also contains the brief overview of the recommendations implemented so far in ProTuS and evaluation experiments executed in the previous work.

2.1. Related work

The focus of distance learning has shifted from basic content delivery towards personalized online learning with intelligent tutoring systems (Latham, Crockett, & McLean, 2014; Mangaroska & Giannakos, 2017). Different techniques and different architecture designs could be used to achieve personalisation in e-learning systems as presented in some earlier publications (Bieliková et al., 2014; Ivanović, Mitrović, Budimac, Vesin, & Jerinić, 2014; Latham, Crockett, McLean, & Edmonds, 2012; Santos & Boticario, 2008; Šimić & Devedžić, 2003; S.; Wu, Ghenniwa, Zhang, & Shen, 2006). Several studies have investigated the anticipated benefits of tag based recommendation (Kim, Alkhaldi, El Saddik, & Jo, 2011; Kurilovas, Kubilinskiene, & Dagiene, 2014; Pirolli & Kairam, 2012; Zervas & Sampson, 2014) and mining sequential patterns within e-learning systems (Chen, Niu, Zhao, & Li, 2014b).

Within the literature covering collaborative tagging in e-learning, there are several existing works that have investigated the expected benefits of tagging when applied in describing educational resources: PLEM (Verpoorten, Chatti, Westera, & Specht, 2010), CROKODIL (Anjorin et al., 2011), SOAF (Cernea, Del Moral, & Labra Gayo, 2008), TaCS (Lavoué, 2012) and TAK system (Chen, Chen, & Sun, 2014a).

Learning resources could be bookmarked, managed in collections and classified using social tagging techniques, as shown in (Verpoorten et al., 2010). The authors presented a social bookmarking service, which acted as an aggregator and filter by supporting learners in retrieving, reusing and sharing learning resources. Authors in (Anjorin et al., 2011) presented a platform that uses contextual information in folksonomies to rank learning resources in a personalized e-learning recommender system. Similar approach for semantic indexing of learning objects from a repository was described in (Cernea et al., 2008). Presented architecture combines automatic techniques of information retrieval with collaborative tagging of documents made by users.

In (Bateman, Brooks, McCalla, & Brusilovsky, 2007), authors investigate how social tagging could be used in education as a support for learning processes with use of Tag-based Collaborative System (TaCS), meant for supporting social and collaborative learning. Tag-based prior knowledge recommendation system was presented in (Chen et al., 2014a,b). The authors showed that a tag-based prior knowledge recommendation tool could help learners retrieve and apply their knowledge effectively and efficiently, and improve their learning performance.

Previously mentioned studies provided evidence that collaborative tagging has the potential to enlarge metadata descriptions of learning resources (Klašnja-Milićevic, Vesin, Ivanović, & Budimac, 2012). It could also be interesting for discovery of learning objects. None of these systems provide original and specially prepared educational material; they merely represent collections of learning resources from different sources available online. These sources are often of low quality, without specifically defined instructional goals. In order to provide efficient tag-based recommendation of resources, these resources need to be prepared, adapted and classified against specific educational goals that an e-learning system aims to achieve. Also, different courses bring specific domain-

Table 1
Functionalities of previous versions of ProTuS.

System's functionalities	Mag	ProTuS	ProTuS 2.0	ProTuS 2.1
Offered courses				
Java online course	x	x	x	x
Web technologies course				x
Features				
Reports on the progress of learners	x	x	x	x
Communication between learners and teachers	x	x	x	x
Interface for adding new learning materials	x	x	x	
Support for additional courses		x	x	x
Visualised reports				x
Semantic web technologies integrated				x
Modular architecture to support addition of new adaptation methods			x	x
Personalisation				
Integrated systems for generating recommendations		x	x	x
Learning style identification		x	x	x
Resource sequencing (navigation patterns mining)		x	x	x
Tag-based recommendation				x
Different presentation methods of teaching material				x
Recommendations based on tags rankings and sequential patterns of learners (hybrid method)				x

related challenges, as learning goals of courses from different domains vary. For example, some courses aim at development of practical skills, while in other students are expected to comprehend or grasp theoretical knowledge. In our approach, we define roles for each learning resource and we categorize tags in order to use them in the personalisation process.

2.2. Existing work with ProTuS

In our previous research, we implemented a generic-purpose framework for a delivery of courses from various domains - ProTuS. ProTuS is the successor of the Mag system that offered introductory programming course with options for online programming (Vesin, Ivanovic, Budimac, & Pribela, 2008). ProTuS introduced several basic personalisation options in the form of RSs and learning styles identification (Klašnja-Milićević, Vesin, Ivanović, Budimac, & Jain, 2017b). The system was completely re-designed and built - using Java and Vaadin framework (Grönroos, 2010), to support easy addition of new personalisation and adaption modules, which resulted with the version 2.0 (Klašnja-Milićević, Vesin, Ivanović, Budimac, & Jain, 2017a,b,c,d). The ProTuS 2.1 version introduced new architecture supported with semantic web technologies (Vesin, Ivanović, Klašnja-Milićević, & Budimac, 2011). This version also introduced one new course (Web technologies) and visualised analytics component. For the experiments presented in this paper, version 2.1 has been used, and the system will be referred to simply as ProTuS system (Table 1).

2.2.1. Recommendation in ProTuS

In order to investigate the usability of different methods for tag-based recommendation in e-learning systems, modular architecture was introduced in ProTuS 2.0 (Klašnja-Milićević, Vesin, Ivanović, & Budimac, 2009). The goal of such architecture was to simplify integration of recommender systems into ProTuS, and to make it adaptive to individual learner's needs and interactions.

The following recommendation methods were implemented and evaluated in previous versions of ProTuS: recommendation based on collaborative filtering was introduced in ProTuS (Klašnja-Milićević, Vesin, Ivanović, Budimac, & Jain, 2017c), recommendation based on learning styles identification along with mining of navigation patterns was introduced in the ProTuS, but fully evolved and improved in version 2.0 (Klašnja-Milićević et al., 2017a,b,c,d), while tag-based recommendation was implemented in Protus 2.1 (Vesin, Klašnja-Milićević, & Ivanović, 2016). The results of experiments, performed with all these versions showed their usability but the best results are gained while combining different approaches and creating hybrid recommendation methods (Klasnja-Milicevic et al., 2016).

2.2.2. Evaluations of ProTuS

Recommendation strategy that included techniques of collaborative filtering and learning style identification was implemented in Protus 2.0 and results were presented in (Klašnja-Milićević, Vesin, Ivanović, & Budimac, 2011). The results of the performed experiments showed the suitability of using this recommendation model, in order to suggest online learning activities.

The implementation of collaborative tagging technique for content recommendation was introduced in Protus 2.1, using the existing modular architecture. This technique was used to provide learners with tag-enabled recommendations of concepts and resources (Vesin et al., 2016). The experiments showed that proposed approach benefits the learners by embedding the additional information in learning resources.

As previous papers provided proofs of usability and potential for using tag-based recommendation in e-learning systems, next step would be to further improve this technique by combining it with other adaptation methods. This paper presents the recommendations based on the system's examination of learners and the collected tags they provided. The experiments have been performed to determine the most efficient recommendation method. After the method has been chosen, it was used in combination with navigational pattern mining to generate recommendations for learners. The details of the process will be presented in the section 4.

3. Recommender systems

Recommender systems can be defined as platforms for providing recommendations to users based on their personal likes and dislikes. These systems use a specific type of information filtering technique that attempts to present to the users those information items (movies, music, books, news, web pages, learning objects, etc.) that they would be interested in (Ricci, Rokach, & Shapira, 2011). Typically, RSs apply personalisation techniques, considering that different users have different preferences and different information needs (Miller, Konstan, & Riedl, 2004).

Collaborative tagging represents an approach for automatic analysis of users' preferences and opinions. To improve recommendation quality, metadata such as content information for items has been typically used as additional knowledge. Collaborative tagging systems allow users to visit provided resources, and to label them with arbitrary words, so-called tags (Golder & Huberman, 2006).

Besides helping users organize their personal collections, a tag also can be regarded as an expression of a user's opinion, while tagging can be considered as an implicit rating or voting on the tagged information resources or items (Liang, Xu, Li, & Nayak, 2008). The innovation with respect to e-learning systems lies in a potential to support learners by recommending tags and learning items, and also by an ability to monitor the learning performances of individual learners (Manouselis, Drachsler, Vuorikari, Hummel, & Koper, 2011).

3.1. RS in e-learning

RSs in e-learning environments differ as the natural learners' behaviour is not separated from other users. They rely on friends, classmates, lecturers, and other sources to make choices for learning. To design an effective RS in e-learning environments, it is important to understand specific learner grouping, their learning activities, choices being made, and learning strategies and goals (Koper & Olivier, 2004). Collaborative tagging systems could allow learners to express their opinions about learning resources, and to label them with arbitrary words, so-called tags (Golder & Huberman, 2006). The innovation that can be achieved by introducing collaborative tagging techniques to e-learning environments lies in their ability to personalize and adjust this content based on the actions of learners and the collected tags (Manouselis & Costopoulou, 2007).

Different tagging algorithms can be used for generating recommendations in e-learning systems (Klašnja-Milićević, Vesin, Ivanović, Budimac, & Jain, 2017a). In this paper, we focus on those that fall within the category of the most-popular tags. Therefore, the proposed approach recommends learning resources based on a generated list of the most popular tags (MP tags) and navigation patterns of learners.

Learners could benefit from entering tags in several important ways: first, tagging is proven to be a meta-cognitive strategy that involves learners in active learning and engages them more effectively in the learning process. As summarized by (Bonifazi, Levialdi, Rizzo, & Trinchese, 2002; Klašnja-Milićević, Ivanović, & Nanopoulos, 2015), tags:

- could help learners to memorize better by highlighting the most significant part of a text,
- could encourage learners to think when they add more ideas to what they are reading, and
- could help learners clarify and make sense of the learning content and concepts being explained.

Learners' tags could create an important trail for other learners to follow by recording their thoughts about a specific learning resource and could give more comprehensible recommendations about the educational material. In e-learning there is a lack of the face-to-face communication that could inform instructors about learners' level of understanding of new concepts. Collaborative tagging, created by learners to categorize learning contents, would allow teachers and instruction designers to reflect on different levels on learners' progress. Tags could be examined at the individual level to investigate a learner's misconceptions and understanding, while tags examined at the group level could identify the overall progress of the class and the quality of the provided educational material. Tagging could help shed light on the perceived benefits of reflection based on tags.

In the rest of this section, we present several different recommendation algorithms for developing tag-based recommendations that fall into *The most popular tags* group, which can be applied and incorporated into e-learning environments. In section 3.1 general tagging folksonomy is presented followed by the overview of *The most popular tags* algorithms (section 3.2). Sections 3.3 and 3.4 present the evaluation of performance of several suitable recommendation techniques in e-learning environments.

3.2. Folksonomy

The term *folksonomy* defines a user-generated and distributed classification system, emerging when large communities of users collectively tag resources (Vander Wal, 2005). Authors in (Hotho, Jäschke, Schmitz, Stumme, & Althoff, 2006) defined a folksonomy as a quadruple $F := (U; T; I; Y)$, where U, T, I are finite sets of instances of users, tags, and items and Y defines a relation, the tag assignment, between these sets, i.e. $Y \subseteq U \times T \times I$.

Folksonomies became popular on the Web with social software applications such as social bookmarking, photo sharing and

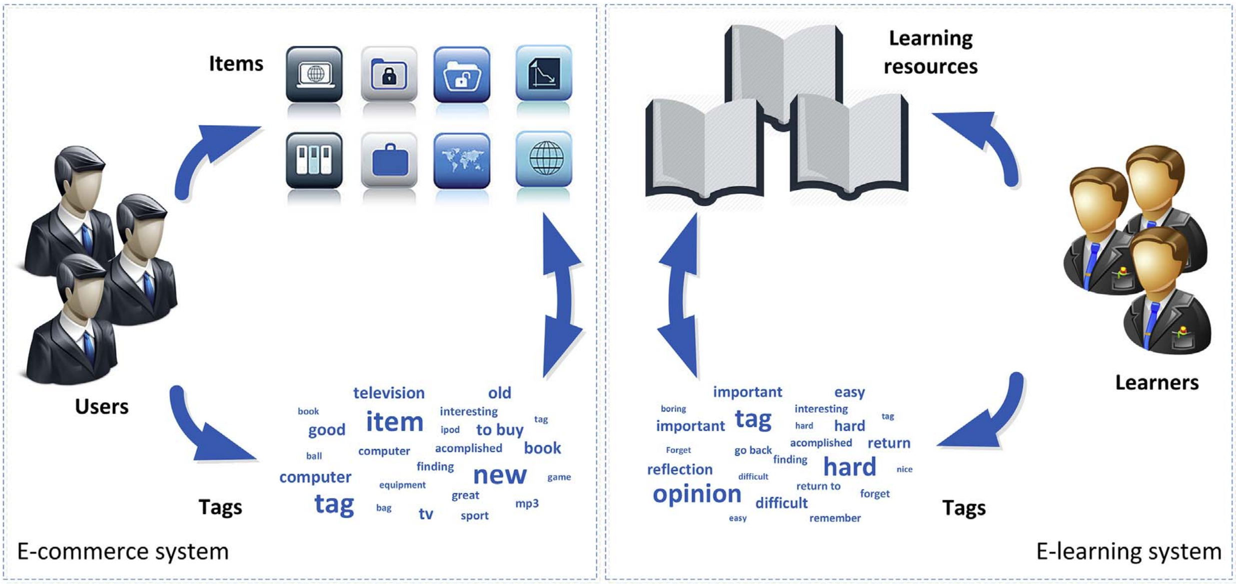

Fig. 1. Mapping of elements within e-commerce and e-learning system.

weblogs. The most obvious benefits are their flexibility, rapid adaptability and free-for-all collaborative customization (Mathes, 2004).

In **tag-based RSs** the recommendations are, for a given user $u \in U$ and a given resource $r \in R$, a set $\hat{T}(u, r) \subseteq T$ of tags. This set represents a recommendation list which is firstly sorted by some quality or relevance criterion, after which the top n elements are selected (Jäschke, Marinho, Hotho, Schmidt-Thieme, & Stumme, 2007).

Collaborative tagging is a powerful mechanism that reveals three-dimensional correlations between users–tags–items. The first adaptation lies in reducing the three-dimensional folksonomy to three two-dimensional contexts: $<$ *user, tag* $>$, $<$ *item, tag* $>$ and $<$ *user, item* $>$. This can be done by augmenting the standard user-item matrix horizontally and vertically with user and item tags correspondingly (Tso-sutter, Marinho, & Schmidt-thieme, 2008). User tags are the tags that user u places on items and are viewed as items in the user-item matrix. Item tags are the tags that describe an item i by users and play the role of users in the user-item matrix.

In order to map this three-dimensional correlation to e-learning systems, we need to identify the basic elements in e-learning and assign them to the elements within an e-commerce system. Therefore, three-dimensional correlation: "users–tags–items" from e-commerce systems maps to correlation: "learners-tags-learning resources" from e-learning systems (Fig. 1).

3.3. Most popular tags

The web algorithms *Most popular tags* are based on tag counts. These methods are easy to compute and that makes them good candidates for online computation of recommendations.

If we want to compute, for a given pair (u, i), the most popular tags of the user u (or the item i), we need to linearly scan the set of all tag assignments Y to calculate the occurrence counts for u's tags (or i's tags) and afterwards sort the gathered tags in descending order by their number (Jäschke et al., 2007).

For a user $u \in U$, the set of all his tag assignments is $Y_u := Y \cap (\{u\} \times T \times I)$. The sets Y_i (for any item $i \in I$) and Y_t (for any tag $t \in T$) are defined accordingly. Similarly, for $t \in T$ and $i \in I$, $Y_{t,u} := Y \cap (\{u\} \times \{t\} \times R)$ and $Y_{t,i} := Y \cap (U \times \{t\} \times \{i\})$ are defined. Finally, for a user $u \in U$, the set of all his/her tags can be defined as $T_u := \{t \in T \mid \exists\, i \in I: (u, t, i) \in Y\}$. The set T_i (for any item $i \in I$) is defined accordingly.

There are three types of *Most popular tags* algorithms (Jäschke et al., 2007):

1. Recommending the most popular tags of the folksonomy is the most simplistic approach. It recommends, for any user $u \in U$ and any item $i \in I$, the same set:

$$\hat{T}(u, i) := \operatorname*{arg\,max}_{t \in T}^{n} (|Y_t|)$$

2. Tags that are specific for an item will be recommended when using the *Most popular tags by item*:

$$\hat{T}(u, i) := \operatorname*{arg\,max}_{t \in T}^{n} (|Y_{t,i}|)$$

3. Since users might have specific interests for which they already tagged several items, using the *Most popular tags by user* is another option:

$$\hat{T}(u,\, i){:}=\arg\max_{t\in T}^{n}(|Y_{t,u}|)$$

where number n represents the overall number of tags.

In general, none of these methods alone provide the best recommendations. Nevertheless, the simplicity and cost efficiency of algorithms based on tag counts make them the preferred approach for use in existing folksonomy systems.

3.4. Mix of Most popular tags recommenders

The main idea of this approach is to recommend a mix of the most popular tags of the user with the most popular tags of the item. The simplest way to mix the tags is to add their counts and then sort them in descending order:

$$\hat{T}(u,\, i){:}=\arg\max_{t\in T}^{n}(|Y_{t,u}| + |Y_{t,i}|)$$

This way of mixing is called *Most popular tags mix 1:1*, since we just add the counts as they are. For instance, if the item has been tagged three times with „popular“ by other users and the user has used the tag „popular“ four times on other items, the tag „popular“ would get a count of seven.

Although this method already yields good results, the influence of the user-based recommendation will be very small compared to the item-based recommendation if many people have tagged this item. On the contrary, if a user has tagged many items, his most popular tags might have counts that are much higher than the counts provided by the items. Therefore, (Jäschke et al., 2007) introduced another mix variant, where the tag counts of the two participating sets are normalized and weighted before they are added. Normalization function is defined for each tag$t \in T_i$:

$$norm_i(t){:}=\frac{|Y_{t,i}|\,\min_{t'\in T}|Y_{t',i}|}{\max_{t'\in T}|Y_{t',i}|\,\min_{t'\in T}|Y_{t',i}|}$$

For $t \in T_u$, the normalization $norm_u(t)$is defined in an analogous manner. After normalization, the weights of all tags in $T_i$and $T_u$lie between zero and one – with the most popular tag(s) having weight 1 and the least important tag(s) having weight 0. A pre-defined factor$\rho \in [0,1]$ allows us to balance the influence of the user and the item:

$$\hat{T}(u,\, i){:}=\arg\max_{t\in T}^{n}(\rho norm_i(t) + (1-\rho) norm_u(t))$$

This method is called *Most Popular Tags ρ– Mix* (Jäschke et al., 2007). ***Most Popular Tags 0 – Mix*** method is just “the most popular tags by user” strategy, since the normalization does not change the order of the tags. Similarly, ***Most Popular Tags 1 – Mix*** is just “the most popular tags by item” strategy. However, due to normalization ***Most Popular Tags 0.5 – Mix*** is not identical to ***Most Popular Tags Mix 1:1***. We will focus on finding an appropriate size of parameter ρin section 6.2.

3.5. Sequential pattern mining

Given a repository of learners' interactions with an e-learning system, the problem of mining sequential patterns is to find the optimal sequence among all the possible learners’ interactions (Chen et al., 2014b). Each of the sequences represents a sequential pattern of learning resources.

A recommendation could be based on the teacher's intended sequence of navigation through the course material or, more interestingly, based on navigation patterns of other successful learners. Information from the collected tags could be used to determine what has been achieved by the particular learning resources or to measure their usefulness and quality. For example, during learning process, a learner reads some useful material and expresses his/her thoughts about the resource with freely chosen tag(s). Assumption is that other learners with similar learning status will have the same experience with these resources.

4. Hybrid method for personalisation of educational resources

In this paper, we present not only the proposed hybrid method, but also an infrastructure for providing this functionality in ProTuS, which facilitates personalized recommendations and makes learning process more successful. The proposed hybrid recommender method, uses principles of sequential pattern mining (described in the Section 3.4) and tag-based recommendations (described in the Sections 3.1–3.3) to recommend learning resources to learner (Agrawal & Srikant, 1995; Chen et al., 2014a,b). It includes five phases that are executed during the learning process (Fig. 2):

1. Learners visit learning resources and express own thoughts and opinions through the tagging interface.
2. Generation of recommended tags lists for every educational resource.
3. Monitoring and recording tagging activities of learners.
4. Rating of the collected tags.

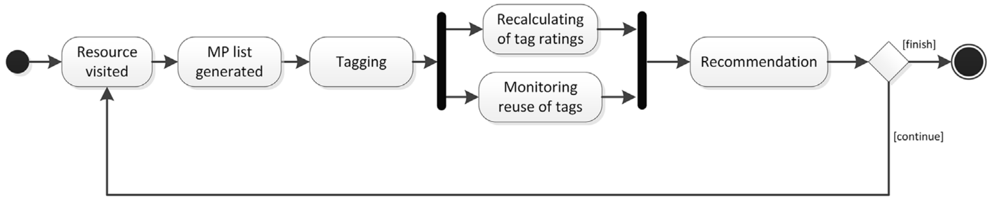

Fig. 2. Phases in the recommendation process.

5. Recommendation process based on tags' rankings and sequential patterns of learners.

The phases are executed sequentially, except the third and fourth, which are executed in parallel. These five phases will be described in the rest of the section in more detail.

Tagging process. This phase includes tagging of educational resources performed by learners. Tagging includes submitting a reflection about the educational resource the learner is currently visiting. The users enter the tags in the tagging interface and the e-learning system records the entered tags for every learning resource and updates the tag repository.

Generating lists of recommended tags based on the most suitable recommendation method. The task of this step is to provide a learner with a personalized ranked list of tags for the visited resource. Two lists are formed and presented to the learner. The first list presents *Most Popular by Item* tag list for the current learning resource, whilst the second list contains *Most Popular Tagsρ- Mix* list. The calculations that are used to generate these lists have been presented in section 3. Precision/recall metric has been used to evaluate the presented techniques and to determine the most appropriate value for ρ. Based on the experimental results showed in section 6.2, learners were presented with two recommendation lists: *Most Popular by Item* tag list and the list based on *Most Popular Tags 0.6- Mix*.

The information provided by tags gives learners and teachers an insight into comprehension and activities of other learners. Tags themselves embed the additional information in learning resources, and thus provide learners with additional information about the visited resources.

Monitoring and recording tagging activities. In order to generate ratings of tags, the system needs to monitor and record the tagging process and track reuse of tags. Rather than entering their own tags, learners can add tags from the two lists generated in the previous phase. Every such reuse of a tag should increase its rating, as these re-used tags represent examples of matching the opinions from different learners. After a user chooses the reuse option from the interface, the system recalculates the rating of tags. Therefore, if multiple learners have reused the same tag for the visited learning resource, that implies that they share the same opinion about that resource and it is more likely that future learners will have the same opinion about it.

Rating of the collected tags. In order to use collected tags in recommendation process, the system needs to filter and calculate their ratings. First, we identified the most generic categories of tags, as tags from different categories have different influence on the learning process. Based on some previous findings on the categories of tags in social tagging systems, we determined an initial set of tag categories by their role and goals (*general*, *technical* and *self-referring*), since not all tags have the same significance for the recommendation process (Bagheri & Ensan, 2016; Kim, Breslin, Chao, & Shu, 2013; Treude & Storey, 2012). The experiments presented in those papers, revealed that tags that explain the usability and usefulness of learning resources (*useful, difficult, not understandable, recommended*, etc.) and those that are self-referring (*return to, cover later, important, for the test*, etc.) have a bigger significance than the more technical ones (*loop use, syntax, task,* etc.). Therefore, we need to exclude the ones that are of low significance (*technical*) from the further recommendation process. This initial selection must be done manually by the teachers, by assigning every tag with the meta-tag of category that it belongs to. Currently, it is done by direct update of the database log, but for the future actions, we plan to develop specialised teacher interface for that purpose. In the further recommendation process, the system will build the repository and automatically select the tags that fall into desired category and should be used in recommendation process.

The goal of the filtering was to discover tags that are usable. If a certain tag falls into the most popular category that does not necessarily mean that it would need to have a high rank. Therefore, tags need to be further ranked by their influence on the learning process.

Tags could be highly ranked from different perspectives. For example, some tags could imply that this resource provides useful material (*nice explanation, clear, recommend*) while some could affect recommendation of the tagged resource negatively (some of the examples are: *useless, not clear, not understandable*, etc.). Therefore, two tags can be recommended as most popular (this was determined by the system as both tags represented common opinion about the resource), but one could imply that resource should be recommended while the other could suggest that the resource is not well prepared or is unclear (which must be determined by the teachers). This practically means that the actual tag rank will be calculated by the system, but the teachers make the final decision on whether the tag's rating receives a positive or a negative sign.

In order to create tag ratings that will be useful for the recommendation process, the system should assign ratings in the range from -1 to 1 to all the tags. A tag with a negative rating contributes negatively to the recommendation status of a resource, while a tag with a positive rating contributes positively to the recommendation status of the resource. The actual rating of the tag is calculated based on the recommendation algorithm and amount of the tag's reuse:

$$R_t = \hat{T}(u, i)\cdot\frac{R(u, i)}{R(i)}$$

Where *T* represents the rank of the tag within the chosen MP tags method, *R(u,i)* represents the amount of its reuse, whilst *R(i)* is the total number of tag reuse for the particular resource.

While visiting (viewing) specific learning resource, opinions (tags) from other learners are provided in the tag lists. Every time learner agrees with opinion (tag) from other learners for the current resource, he/she can choose that tag from recommended lists and add it to his/her own personal list. Every such reuse is automatically monitored and recorded by the system. After every reuse of particular tag, the system recalculates its value, and updates the rating of that tag in the database. These ratings are used in the further recommendation process to generate recommendations for other learners.

Hybrid recommendation process. Recommendation process includes generation of suggested sequential pattern of learning resources for the current learner. The proposed algorithm filters educational resources according to tag ratings in order to propose the next resource to visit. We used the weighted hybrid strategy (Chen et al., 2014a,b), which gives each resource a certain weight and accumulates the weights for each of them. The details of the process are described in detail in the paragraphs bellow.

Weight of the resource represents the product of all assigned tags rating:

$$W_i = \prod_{k=1}^{m} r_k$$

Where r_k represents the rank of tags (calculated by the system) for the resource, while *m* is the overall number of resources. Protus calculates and stores values W(i) for every resource. These weights represent a decimal value between zero and one, with 1 (one) meaning the resource is highly recommended and 0 (zero) meaning the resource is not likely to be recommended. Lastly, the system accumulates the weight of each resource and orders the resources by their weights.

The weighted method suggests the possible sequence pattern of resources to be recommended. The sequential patterns for each learner are generated and the resources within the same lecture are rearranged within tabs based on their weights in descending order. The resource with the next highest weight is presented when the learner chooses "Next resource" option.

5. ProTuS – programming tutoring system

Protus is designed to provide learners with personalized courses from various domains. It allows learners to browse educational material and test their knowledge. We have implemented the recommendation component of the ProTuS that recommends (Vesin et al., 2016):

1. The most popular tags for every educational resource,
2. The sequence of educational resources that should be presented to the learner based on their ratings.

5.1. The architecture of ProTuS

The ultimate goals of developing ProTuS have been increasing learning opportunities, improved dealing with challenges and increasing efficiency. The implemented framework for building automatic recommendations with our newly proposed hybrid method in ProTuS is composed of three tiers (Fig. 3):

Learner-system interaction module, which collects and pre-processes data about learners' interactions and builds learner models based on the collected data. The data about visited resources and lectures, test results and earned grades is collected within this module and saved into the data storage. This module also collects all information about the tagging process for every learner and updates the tag repository that is used for tag-based recommendation.

Recommendation module, which uses data from *Learner model* and *Tag repository* to generate recommendations based on tags rankings and sequential patterns of learners. This module consists of several components:

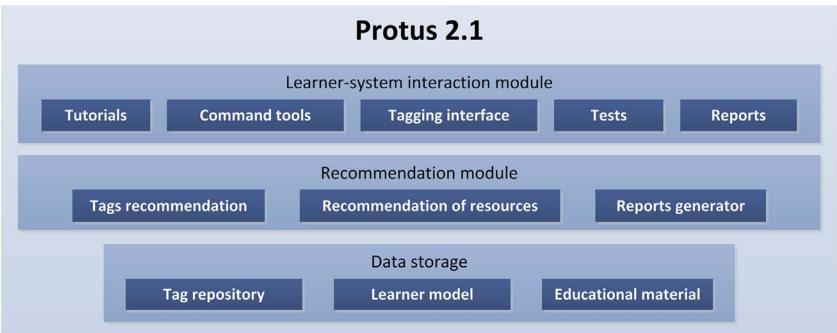

Fig. 3. ProTuS architecture.

- *Tags recommendation* - calculates the most popular lists and tags ratings.
- *Recommendation of resources* - calculates weight for every resource and creates sequences in which they will be presented to the learner.
- *Reports generator* - generates various reports about overall tags usage, learners' interaction, test results, etc. These reports contain the data specific for a learner as well as overall overview of all active learners.

Data storage module, which stores data relevant to perform the recommendation process, separated in three categories:

- *Educational material* – represents the collection of learning (educational) resources.
- *Tag repository* – records all entered tags and their ranking and categorisation. Categorisation process (which is currently done manually) has a purpose of identifying the categories of the most popular tags (*general*, *technical* and *self-referring*).
- *Learner model* **–** a collection of both static and dynamic data about the learner. The system uses that information to predict the learner's behaviour, and thereby adapt educational material to his/her individual needs. The e-learning system gradually re-builds the learner model during learning sessions in order to keep track of the learner's actions and his/her progress, to detect and correct his/her errors and possibly to redirect the session accordingly.

Modular architecture of ProTuS allows easy update of the system and addition of new components and features. In order to implement the hybrid method presented in this paper, the following components were implemented:

1. **Learner-system interaction module** was expanded with the tagging interface for students, and the component that records every tagging action.
2. **Recommendation module** with its components.
3. **Data storage module** has been expanded with the tag repository.

The goal of such architecture was to provide an environment to experimentally evaluate the effects of proposed hybrid recommendation method and investigate the possibilities for use of the tag-based recommendation in a practically used and exploited e-learning environment.

5.2. Learning material in ProTuS

In ProTuS, we implemented a concept where different resources are responsible to achieve specific goals. For example, every resource has defined purpose – to introduce a topic, provide additional information, clarify some topic, or explain a topic in a different way. These resources are recommended according to the results of mapping specific resources to specific goals. These goals are further determined by tags provided by learners.

Practically, that results in the following organisation of the educational material in ProTuS. Educational material is divided into courses, each of which consists of a sequence of lessons (Fig. 4). Every lesson contains several resources (presented in different tabs) with predefined specific roles: introduction, fact, theory, explanation, example, syntax, etc. For example, a resource that has “fact” or “definition” role is used to increase basic knowledge. A resource with “example” role is used to increase learner's practical skills. Also, some resources represent the crucial information, while the others represent just a mean to provide additional information or a comparison.

The resources within one lecture are presented to a learner in the default order (as defined by the course author) at the beginning. For the programming domain, the order is following: *Introduction*, *Basic information*, *Theory*, *Syntax rules*, *Explanation*, *Examples*, *Activity* and *Tasks*. It is also possible to assign multiple resources the same role for one lecture. After the weights of resources have been calculated (as presented in the section 4), their order is updated. Therefore, a learning resource that has been tagged by highly ranked tags (useful from the point of view of reaching the specific learning goals) will be assigned a high value and therefore will be positioned higher in the recommendation lists for the current learner. Naturally, resources that represent introduction and basic

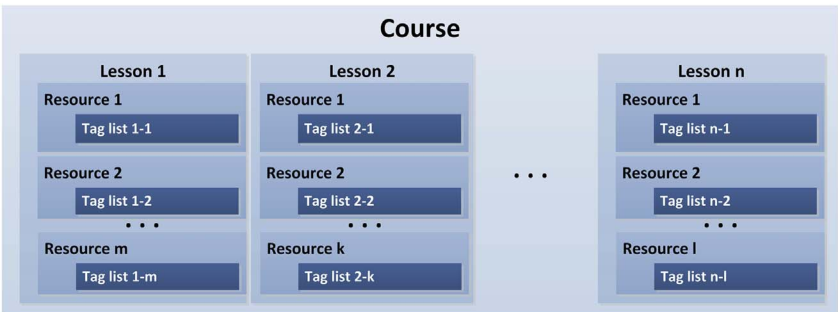

Fig. 4. Organisation of resources.

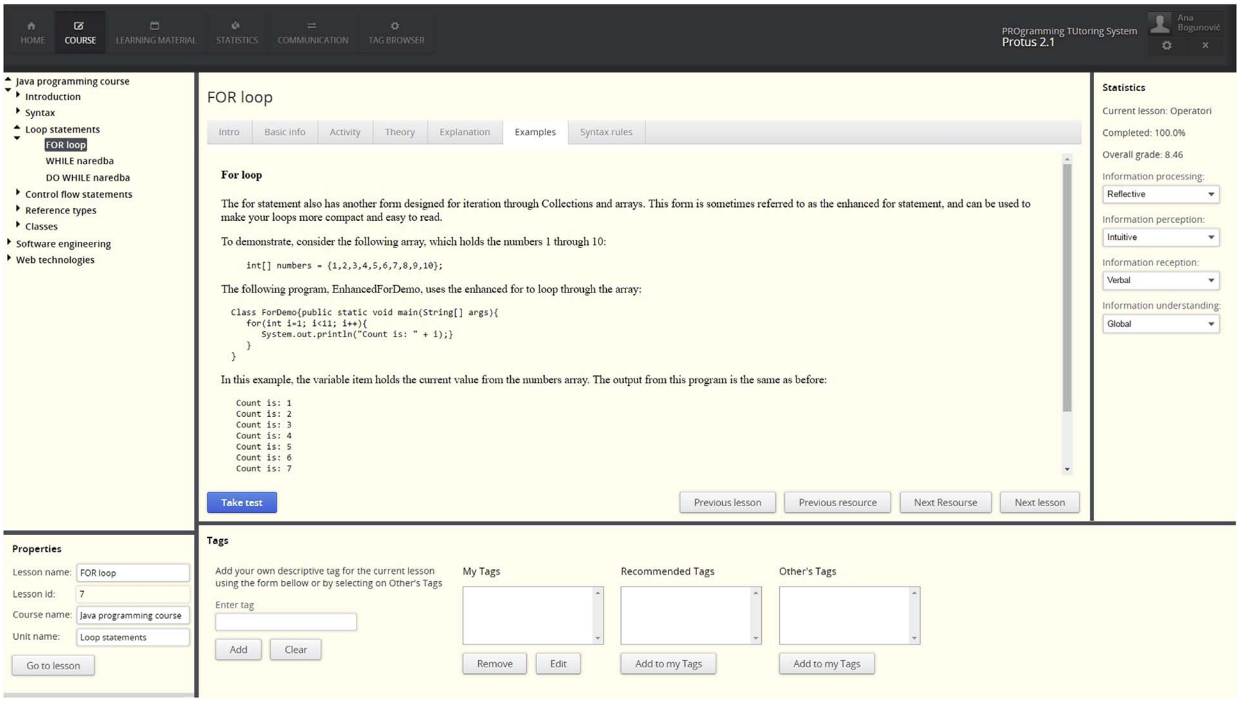

Fig. 5. User interface of ProTuS.

information about the lecture should be always at the beginning, but the order of others depends on the topic being taught, preferences of learners or the nature of the lecture. Sometimes, learners prefer to learn about the basic concepts first before they try to solve some tasks, whilst sometimes they prefer to learn by solving problems. With the proposed method, order of resources is created based on the opinions of other learners. In future research, our plan is to recommend the navigation patterns of resources based on the learning goals that were determined for the learner (these goals can be defined by the system or by the learner himself).

5.3. *Learner's interface*

Learners attend courses through the web interface implemented in ProTuS system. The user interface of this system offers the following functionalities (Fig. 5):

- review of the offered courses and teaching materials,
- testing of knowledge,
- communication with the mentor and other learners,
- various display formats of teaching materials,
- reports about progress, test results, and provided courses and lectures.

5.4. *Tagging interface in ProTuS system*

Along with the presentation of resources to learner, the user interface in ProTuS also contains options for creating and reviewing tags for every resource. Therefore, learners can enter tags for every provided learning resource and in that way, express their thoughts about it.

Whenever a learner returns to a particular learning object, the list of tags he/she has previously made will re-appear (Fig. 6).

To create a tag in ProTuS the learner simply enters arbitrary keywords in the appropriate field.

Recommended tags list presents the most popular tags added to the current resource by other learners. According to the research that we have made by comparative analysis of tag-based recommender algorithms, the recommended tags list is generated according to *Most Popular Tags - Mix* model. The list of the most frequently used tags for the visited resource is given in the *Other's tags* list. The learner has the ability to add any tags from the *Others' tags* and *Recommended tags* to *My tags* list. These actions are monitored in order to recognise the most used tags and calculate their rankings accordingly. The learner can use these lists of recommended tags to see reflections of other learners about the specific learning resource as well.

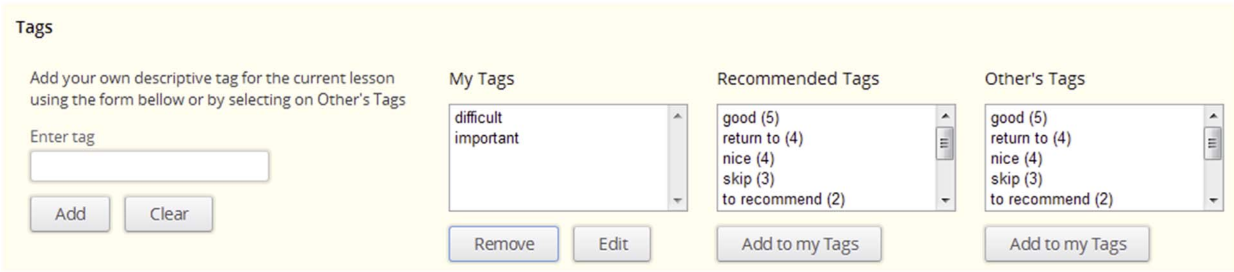

Fig. 6. Tags menu.

6. Evaluation

In order to evaluate the hybrid method, we performed the experiments in three phases:

1. Implementation of the ProTuS components, necessary for the execution of the proposed hybrid approach (as explained in the Section 5.1)
2. Evaluation of the recommendation techniques performance. The goal of this experiment was to determine the most suitable tag recommendation method that will generate the lists of recommended tags for every learning resource. The classical metrics precision and recall were used to evaluate the performance of recommendation techniques in e-learning environments.
3. Analysis of satisfaction with ProTuS system. In order to test the tagging interface and activities of the learners, we conducted an experiment with a group of students at the Centre for young talents in Novi Sad. The students used the ProTuS system for learning Java programming basics.

6.1. *Experimental protocol and evaluation metrics*

The original dataset contains 3.683 tags from 120 learners on 62 learning objects. The performance of the presented algorithms is evaluated by treating a part of the data set as ground-truth data (the test set), and building prediction models from the remaining data (the training set). We randomly divided the data set into a training set and a test set with sizes 80 and 20 percent, respectively. As performance measures for item and tag recommendations, we used the classic metrics of precision and recall which are standard in such scenarios (Herlocker, Konstan, Terveen, & Riedl, 2004). Precision and recall have been used to evaluate information retrieval systems for many years. Within the RS context, precision and recall have the following definitions regarding the evaluation of top-N recommendations: for a test user that receives a list of N recommended tags (top-N list), with i being the item from the randomly picked post of user u and $\hat{T}(u, i)$the set of recommended tags, recall and precision can be calculated as:

$$precision(\hat{T}(u, i)) = \frac{1}{|U|} \sum_{u \in U} \frac{|tags(u, i) \cap \hat{T}(u, i)|}{|\hat{T}(u, i)|}$$

$$recall(\hat{T}(u, i)) = \frac{1}{|U|} \sum_{u \in U} \frac{|tags(u, i) \cap \hat{T}(u, i)|}{|tags(u, i)|}$$

Precision is the ratio of the number of relevant tags in the top-N list (i.e., those in the top-N list that belong in the future set of tags posted by the test user) to N.

Recall is the ratio of the number of relevant tags in the top-N list to the total number of relevant tags (all tags in the future set posted by the test user).

6.2. *Evaluation of the performance of recommendation techniques*

The classical metrics precision and recall were used to evaluate the performance of recommendation techniques in e-learning environments. First, we describe the specific settings used to run evaluated algorithms. Then we present and discuss the results of evaluation of proposed method in our e-learning system.

Before starting full experimental evaluation of the selected algorithms (presented in the section 3.2 and 3.3) we first needed to determine the sensitivity of appropriate parameters to different algorithms and from the sensitivity plots. We fixed the optimal values of these parameters and used them for the rest of the experiments.

Most Popular Tags. We counted the overall number of tags that are posted in the whole system (regardless of the resource being tagged) and used the top tags as recommendations.

Most Popular Tags by Item. For a given item we counted in how many posts each tag occurs together with that item. We then used the tags that the most often occurred together with that item as a recommendation.

Most Popular Tagsρ- Mix. Before comparing *Most Popular Tagsρ- Mix algorithm* with the others, we focused on finding an appropriate size of parameterρ. To achieve this we observed similar precision/recall behaviour for all values of$\rho \in \{0, \ 0.1, \ ..., \ 0.9, \ 1\}$. As

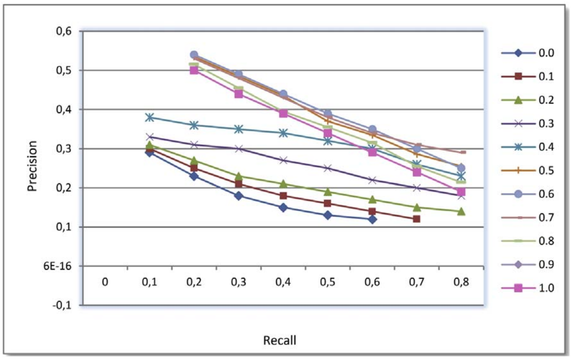

Fig. 7. Precision and recall of most popular tags ρmix for $\rho \in \{0, \ 0.1, \ ..., \ 0.9, \ 1\}$.

can be seen in Fig. 7, variation of algorithm with the most popular tags by user ($\rho = 0$) performs worse than variation of algorithm with the most popular tags by item($\rho = 1$)for all numbers of recommended tags. All mixed versions perform better than *Most popular tags by user* and all mixed versions with $\rho \geq 0.5$ perform better than *Most popular tags by item*. The best performance is obtained if$\rho = 0.6$.

In order to compare *Most popular tags* algorithms, we used usual precision/recall plots (Fig. 8). All algorithms perform significantly better than the baseline *Most Popular Tags* and the *Most Popular Tags by User* strategy. In contrast to these two approaches, *Most Popular Tagsρ*Mix - recommender includes the user's tags in the recommendations as well. As the diagrams show, it is successful and could yield results better than other *MP* algorithms. Better results are achieved by adding a small amount of popular tags of the user to the tags from the item, which increases both precision and recall.

6.3. Analysis of satisfaction with ProTuS system

A group of 65 students was chosen for this experiment and they were asked to use and test the system. They used ProTuS system for six weeks for learning Java and they were encouraged to use the tagging interface of ProTuS and to express their thoughts and opinions by tagging learning resources. Tagging practices of students have been investigated and identified and the results were presented in (Vesin et al., 2016). Use of tags has been increasing over a testing period, and tags concerning the usability and usefulness of learning resources (useful, difficult, not understandable, recommend, etc.) were used rather than more technical (loop use, syntax, task. etc.) or self-referring ones (return to, cover later, important, for the test, etc.).

In order to evaluate the proposed method, we performed the evaluation of the tagging system according to the individual satisfaction of learners with the given recommendations. Satisfaction is closely related to the motivation of the learner and therefore it is a rather important measure for learning. To get subjective evaluation of our system, at the end of the course we organized a non-mandatory questionnaire that collected learners' opinions about the main features of the system. The questions were mostly concerned with the implemented tagging functionality and the benefits it brings to learners. The results of the questionnaire were used to improve the quality of lessons. This questionnaire (Table 2) maps a set of 16 questions over 4 dimensions: ‘ease of tagging’, ‘usefulness of tagging’, ‘usefulness of the ProTuS system and tag exchange’, and ‘ProTuS system is user-friendly’.

Participants are asked to give a level of agreement to each question on a 1-to-5 scale (strongly disagree, disagree, neutral, agree, and strongly agree). For example, the fifth question in Table 2 is about the relevance and unexpectedness of tags suggested by the ProTuS. A response of 1 would mean that the learner strongly disagrees, while 5 would mean that the learner strongly agrees with statement: “the tags suggested by the ProTuS are both relevant and unexpected”.

To examine the internal consistency and content validity of this survey, Cronbach's alpha coefficient was calculated for the 20-

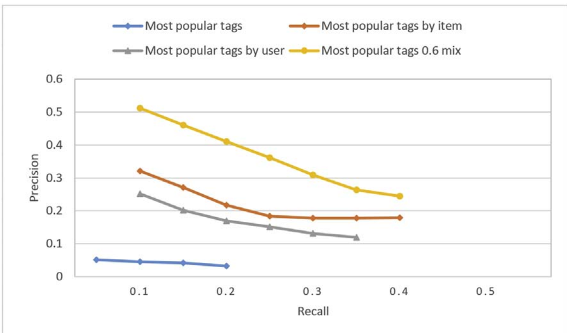

Fig. 8. Recall and Precision for the MP tags.

Table 2
Questionnaire - Analysis of satisfaction with ProTuS system.

Question	Response				
	1	2	3	4	5
1. I can easily construct meaningful words or phrases to represent the learning objects with tags.					
2. The meanings of tags which describe the learning objects are clear.					
3. The proposed tags allow me to express the right term when entering tags.					
4. Reviews of my previous own tags facilitate the recall of learning objects' ideas and information.					
5. The tags suggested by the ProTuS were useful to comprehend the material.					
6. I am comfortable with others knowing what I think about learning object.					
7. I am interested in finding out who else feels similarly to me regarding specific topics.					
8. Having a high level of influence on my neighbours is important to me.					
9. I think that using tags enables me to easily grasp the structure and concepts of learning objects.					
10. I think that usage of tagging information provides me with effective feedback during the learning process.					
11. The tagging activities inspire me to form new ideas.					
12. I think that ProTuS's user interface is simple to learn.					
13. I can start quickly with the ProTuS system.					
14. I believe that ProTuS is effective at learning my preferences.					
15. I am satisfied with ProTuS's recommendations.					
16. I trust that ProTuS has the ability to make correct recommendations for me.					

item questionnaire. Cronbach's α (alpha) (Bland & Altman, 1997) is a coefficient of reliability. It is usually used as a measure of the internal stability or consistency of a psychometric test score for a sample of examinees. It was first named alpha by Lee Cronbach in 1951, as he had intended to continue with further coefficients. Alpha is not robust against omitted data. Several other Greek letters have been used by later researchers to assign other measures used in a similar context (Cortina, 1993). Cronbach's α is defined as:

$$\alpha = \frac{K}{K-1}\left(1 - \frac{\sum_{i=1}^{K}\sigma_{Y_i}^2}{\sigma_X^2}\right)$$

where K is the number of *items* or *testlets*, σ_X^2 is the variance of the observed entire test scores, and $\sigma_{Y_i}^2$ the variance of item i for the current sample of persons (DeVellis, 1991). In order to determine if a question item is correlated with a factor, we applied the distinguish validity test by using the factor analysis method to observe each question item. Four factors among these items are shown in Table 3. The eigenvalues of the four factors are greater than 1.00 with variance 68.12% explained. From the experimental results, it was found that some question items were not correlated with factors (that is, their load was less than 0.5). As a result, 4 questions items were dropped, reducing the overall number to 16. In addition, the experiment shows that the internal reliability indexes of the four factors are 0.776, 0.833, 0.716, and 0.768, respectively.

The alpha coefficient was 0.814 after deleting non-correlated factors. Therefore, the obtained results suggest that these factors were sufficiently reliable for representing learner tagging behaviours, when the Cronbach's α is higher than 0.7 (Hwang, Tsai, Tsai, & Tseng, 2008; Nunnally & Bernstein, 1994).

Table 3
Rotated factor loadings and Cronbach's α value for four factors.

Items	Factor1	Factor2	Factor3	Factor4
Factor 1: Easy to tagging α = 0.776				
I_1	0.672			
I_2	0.727			
I_3	0.812			
Factor 1: Usefulness of tagging α = 0.833				
I_6		0.614		
I_7		0.718		
I_8		0.588		
Factor 1: Usefulness of tagging α = 0.716				
I_9			0.731	
I_{10}			0.708	
I_{11}			0.645	
I_{12}			0.811	
Factor 1: Usefulness of tagging α = 0.768				
I_{15}				0.871
I_{16}				0.738
I_{17}				0.645
I_{18}				0.821
I_{19}				0.672

α = 0.814, total variance explained is 68,12%.

Table 4
Statistical results of the questionnaire for evaluating the ProTuS system.

Questionnaire item (four factors)	Strongly disagree (%)	Disagree (%)	Neutral (%)	Agree (%)	Strongly agree (%)
Easy to tagging in ProTuS	–	16.81	42.19	38.31	2.69
Usefulness of tagging in ProTuS	–	4.35	27.19	53.14	15.32
Usefulness of ProTuS system	–	–	25.71	68.1	6.19
ProTuS is user friendly	–	–	46	47.8	6.1

The statistical analysis of the survey results is summarized in Table 4. Among 65 students, in total 45 completed the survey. The major findings are presented as follows:

(1) 97% of the learners indicated that creating tags was easy, and that it was easy to construct meaningful words or phrases to represent the learning objects with tagging objects.
(2) 85% of the learners thought that tagging activity can help learners summarize new ideas and quickly grasp the structure and concepts. Some learners indicated that their tags were more accurate after sufficient tagging practice.
(3) 93% of the learners agreed that ProTuS is capable of helping them to easily comprehend the context of learning objects, and can help them improve their learning efficiency.
(4) 94% of the learners regarded that ProTuS system is user friendly.

7. Discussion

In this paper, we presented a recommendation method for personalisation in e-learning that involves use of *Most popular tags* algorithms. The proposed hybrid recommendation method extends the application of social tagging by using the collected tags for recommendation of learning resources. The presented method was implemented and tested within existing programming tutoring system.

ProTuS was extended with components that allow building and update of tags repository and generate recommendations based on the data extracted from it. As a result, the system was enhanced with features that generate sequences of educational material to be presented to learners based on their influence on the learning process and educational goals.

During the experiment, we compared different recommendation methods based on counting of the most popular tags (section 6.2). Experimental results provided evidence that different types of *Most Popular Tags* algorithms can be applied to e-learning environments to provide better recommendation capabilities. Overall conclusion was that the *Most Popular Tags 0,6 Mix* recommender is the most successful and could yield results better than other most popular tactics. Therefore, learners were presented with this recommended list of tags in the learning process. Later during learning process, learners used this list to find opinions of other learners which match their own.

We analysed the potential of collaborative tagging systems and implemented the hybrid method for generating recommendations based on social tagging and resource sequencing. Several adaptations were made for the proposed approach to be suitable for the e-learning environment. The results of the performed experiment show overall satisfaction of the learners with the proposed approach.

This study provided evidence about potential of social tagging of resources to enlarge their metadata descriptions, and for improving search and recommendation of educational resources. Implemented tag-based interface of ProTuS provides opportunities for learners to interpret contents of learning resources and find knowledge connections. Tagging certain activities can help learners summarize new ideas and quickly grasp the structure and concepts presented during the course. Tags also helped learners to comprehend the context of learning objects, and to improve their learning efficiency. The information about the learners' on-line communication and collaboration activities can be used to make decisions about further teaching strategy.

Although the recommendation of lessons, learning material and resources could be achieved through tagging, the efficiency and effectiveness of this method largely rely on the willingness of the learners to express their thoughts and tag the resources.

8. Conclusion

RSs have gained a huge popularity over the last years when numerous new advanced methods and technics were proposed and many popular systems have been developed. However, despite all the progress being made, RS still needs further improvements to make recommendation tactics more effective in a broader range of applications. With the increasing popularity of the collaborative tagging systems, tags could become interesting and useful information to enhance RS algorithms. Besides helping users to organize their personal collections, tags also can be regarded as expressions of users' opinions, while tagging can be considered as implicit rating or voting on the tagged information or items. Thus, the tagging information can be used to make recommendations.

Learners could benefit from writing tags in several important ways. Tagging is proven to be a meta-cognitive strategy in educational processes that involves learners in active learning and engages them more effectively in the learning activities. Tags could help learners to memorize better by highlighting the most significant part of a text, could encourage learners to think when they add more ideas to what they are reading, and could help learners clarify and make sense of the learning content whilst they try to reshape the information. Learners' tags could create an important trail for other learners to follow as they record learners' thoughts about specific learning material and could give more comprehensible recommendations about the learning process. Tags presented on a webpage can give a learner some idea of its importance and its content.

The hybrid recommendation method was proposed in this paper that collects the opinions from the users and uses them to generate recommendation of sequence of learning resources that will be presented to the learner. The proposed algorithm filters educational resources by assigning and accumulating the weights for each of them.

The goal of this paper was to evaluate the usability of proposed hybrid method by its implementation in programming tutoring system. We performed the experiments to determine the most efficient recommendation method and identify the level of learner's satisfaction with the e-learning system. The experiments showed that implemented tagging interface of ProTuS helps the learners by adding the supplementary information in learning resources, and provides them with the opinions of other peers.

This research also suggests new ideas for personalized recommendations and outlines a great number of challenges for future work. One of the goals is implementation of the full automatization of categorisation of tags that is currently done manually. Even though the Java programming course was chosen as the illustrative example and used in the experimental evaluation, it is feasible that with adequate programming effort, ProTuS could be used for other knowledge domains.

References

Agrawal, R., & Srikant, R. (1995). Mining sequential patterns. In data engineering, 1995. *Proceedings of the Eleventh international conference on (pp. 3–14)*.

Anjorin, M., Rensing, C., Bischoff, K., Bogner, C., Lehmann, L., Reger, A. L., ... Domínguez García, R. (2011). CROKODIL - a platform for collaborative resource-based learning. *Lecture notes in computer science (including subseries lecture notes in artificial intelligence and lecture notes in bioinformatics): Vol. 6964*, (pp. 29–42). . LNCS https://doi.org/10.1007/978-3-642-23985-4_4.

Bagheri, E., & Ensan, F. (2016). Semantic tagging and linking of software engineering social content. *Automated Software Engineering, 23*(2), 147–190. https://doi.org/10.1007/s10515-014-0146-2.

Balabanović, M., & Shoham, Y. (1997). Fab: Content-based, collaborative recommendation. *Communications of the ACM*. https://doi.org/10.1145/245108.245124.

Bateman, S., Brooks, C., McCalla, G., & Brusilovsky, P. (2007). Applying collaborative tagging to e-learning. *WWW,* 1–7. https://doi.org/10.1.1.64.8892.

Bieliková, M., Šimko, M., Barla, M., Tvarožek, J., Labaj, M., Móro, R., ... Ševcech, J. (2014). ALEF: From application to platform for adaptive collaborative learning. *Recommender Systems for Technology Enhanced Learning,* 195–225.

Bland, J. M., & Altman, D. G. (1997). Statistics notes: Cronbach's alpha. *Bmj, 314*(7080), 572.

Bonifazi, F., Levialdi, S., Rizzo, P., & Trinchese, R. (2002). A web-based annotation tool supporting e-learning. *Proceedings of the Working Conference on Advanced Visual Interfaces - AVI '02, 123*https://doi.org/10.1145/1556262.1556281.

Cernea, D. A., Del Moral, E., & Labra Gayo, J. E. (2008). SOAF: Semantic indexing system based on collaborative tagging. *Interdisciplinary Journal of Knowledge & Learning Objects, 4*, 137–149.

Chen, J.-M., Chen, M.-C., & Sun, Y. S. (2014a). A tag based learning approach to knowledge acquisition for constructing prior knowledge and enhancing student reading comprehension. *Computers & Education, 70*, 256–268. https://doi.org/10.1016/j.compedu.2013.09.002.

Chen, W., Niu, Z., Zhao, X., & Li, Y. (2014b). A hybrid recommendation algorithm adapted in e-learning environments. *World Wide Web, 17*(2), 271–284.

Cheung, K. W., Kwok, J. T., Law, M. H., & Tsui, K. C. (2003). Mining customer product ratings for personalized marketing. *Decision Support Systems, 35*(2), 231–243. https://doi.org/10.1016/S0167-9236(02)00108-2.

Cortina, J. M. (1993). What is coefficient alpha? An examination of theory and applications. *Journal of Applied Psychology*. https://doi.org/10.1037/0021-9010.78.1.98.

DeVellis, R. F. (1991). Guidelines in scale development. *Scale Development* (pp. 51–60). .

Golder, S. A., & Huberman, B. A. (2006). Usage patterns of collaborative tagging systems. *Journal of Information Science, 32*(2), 198–208.

Grönroos, M. (2010). *Book of Vaadin: Vaadin 6.4.* Writing.

Herlocker, J. L., Konstan, J. A., Terveen, L. G., & Riedl, J. T. (2004). Evaluating collaborative filtering recommender systems. *ACM Transactions on Information Systems*. https://doi.org/10.1145/963770.963772.

Hotho, A., Jäschke, R., Schmitz, C., Stumme, G., & Althoff, K.-D. (2006). Folkrank: A ranking algorithm for folksonomies. *LWA: Vol. 1*, (pp. 111–114).

Hwang, G.-J., Tsai, P.-S., Tsai, C.-C., & Tseng, J. C. R. (2008). A novel approach for assisting teachers in analyzing student web-searching behaviors. *Computers & Education, 51*(2), 926–938.

Ivanović, M., Mitrović, D., Budimac, Z., Vesin, B., & Jerinić, L. (2014). Different roles of agents in personalized programming learning environment. *New horizons in web based learning: Vol. 7697*, (pp. 161–170). Springer LNCS.

Jäschke, R., Marinho, L., Hotho, A., Schmidt-Thieme, L., & Stumme, G. (2007). Tag recommendations in folksonomies. *Knowledge discovery in databases: PKDD 2007 SE - 52: Vol. 4702*, (pp. 506–514). . https://doi.org/10.1007/978-3-540-74976-9_52.

Kim, H. N., Alkhaldi, A., El Saddik, A., & Jo, G. S. (2011). Collaborative user modeling with user-generated tags for social recommender systems. *Expert Systems with Applications, 38*, 8488–8496. https://doi.org/10.1016/j.eswa.2011.01.048.

Kim, H.-L., Breslin, J. G., Chao, H.-C., & Shu, L. (2013). Evolution of social networks based on tagging practices. *Services Computing, IEEE Transactions on, 6*(2), 252–261. https://doi.org/10.1109/TSC.2011.54.

Klašnja-Milićević, A., Ivanović, M., & Nanopoulos, A. (2015). Recommender systems in e-learning environments: A survey of the state-of-the-art and possible extensions. *Artificial Intelligence Review, 44*(4), 571–604.

Klašnja-Milićević, A., Vesin, B., Ivanović, M., & Budimac, Z. (2009). Integration of recommendations into Java tutoring system. *The 4th international conference on information technology ICIT 2009 Jordan*.

Klašnja-Milićević, A., Vesin, B., Ivanović, M., & Budimac, Z. (2011). E-Learning personalization based on hybrid recommendation strategy and learning style identification. *Computers and Education, 56*(3), 885–899.

Klašnja-Milićevic, A., Vesin, B., Ivanović, M., & Budimac, Z. (2012). Personalisation of programming tutoring system using tag-based recommender systems. *Proceedings of the 12th IEEE international conference on advanced learning technologies, ICALT 2012* (pp. 666–667). .

Klašnja-Milićević, A., Vesin, B., Ivanović, M., Budimac, Z., & Jain, L. C. (2017a). Design, architecture and interface of Protus 2.1 system. *E-Learning systems* (pp. 185–212). Springer International Publishing.

Klašnja-Milićević, A., Vesin, B., Ivanović, M., Budimac, Z., & Jain, L. C. (2017b). Folksonomy and tag-based recommender systems in e-learning environments. *E-Learning systems* (pp. 77–112). Springer International Publishing.

Klašnja-Milićević, A., Vesin, B., Ivanović, M., Budimac, Z., & Jain, L. C. (2017c). Personalization in Protus 2.1 system. *E-Learning systems* (pp. 213–257). Springer International Publishing.

Klašnja-Milićević, A., Vesin, B., Ivanović, M., Budimac, Z., & Jain, L. C. (2017d). Recommender systems in e-learning environments. *E-Learning systems* (pp. 51–75). Springer International Publishing.

Klasnja-Milicevic, A., Vesin, B., Ivanovic, M., Budimac, Z., Jain, L. C., Klasnja-Milievié, A., ... Jain, L. C. (2016). *E-Learning systems: Intelligent techniques for personalization*.

Koper, R., & Olivier, B. (2004). Representing the learning design of units of learning. *Journal of Educational Technology & Society, 7*(3).

Kurilovas, E., Kubilinskiene, S., & Dagiene, V. (2014). Web 3.0-Based personalisation of learning objects in virtual learning environments. *Computers in Human*

Behavior, 30, 654–662. https://doi.org/10.1016/j.chb.2013.07.039.
Latham, A., Crockett, K., & McLean, D. (2014). An adaptation algorithm for an intelligent natural language tutoring system. *Computers and Education, 71*, 97–110. https://doi.org/10.1016/j.compedu.2013.09.014.
Latham, A., Crockett, K., McLean, D., & Edmonds, B. (2012). A conversational intelligent tutoring system to automatically predict learning styles. *Computers and Education, 59*(1), 95–109. https://doi.org/10.1016/j.compedu.2011.11.001.
Lavoué, E. (2012). Towards social learning games. *Proceedings of the 11th international conference on web-based learning (ICWL 2012)* (pp. 168–177). .
Liang, H., Xu, Y., Li, Y., & Nayak, R. (2008). Collaborative filtering recommender systems using tag information. *Proceedings - 2008 IEEE/WIC/ACM international conference on web intelligence and intelligent agent technology - workshops, WI-IAT workshops 2008* (pp. 59–62). . https://doi.org/10.1109/WIIAT.2008.97.
Mangaroska, K., & Giannakos, M. (2017). Learning analytics for learning Design: Towards evidence-driven decisions to enhance learning. *European conference on technology enhanced learning* (pp. 428–433). .
Manouselis, N., & Costopoulou, C. (2007). Experimental analysis of design choices in multiattribute utility collaborative filtering. *International Journal of Pattern Recognition and Artificial Intelligence, 21*(2), 311–313. https://doi.org/10.1142/S021800140700548X.
Manouselis, N., Drachsler, H., Vuorikari, R., Hummel, H., & Koper, R. (2011). Recommender systems in technology enhanced learning. *Recommender systems handbook* (pp. 387–415). . https://doi.org/10.1007/978-0-387-85820-3.
Mathes, A. (2004). Folksonomies – cooperative classification and communication through shared metadata. *Computer Mediated Communication - LIS590CMC,* 1–13. https://doi.org/10.1.1.135.1000.
Miller, B. N., Konstan, J. A., & Riedl, J. (2004). PocketLens : Toward a Personal Recommender System. *ACM Transactions on Information Systems, 22*(3), 437–476. https://doi.org/10.1145/1010614.1010618.
Nunnally, J. C., & Bernstein, I. (1994). Psychometric theory. *rdsepiucsforg: Vol. 3*https://doi.org/10.1037/018882.
Pirolli, P., & Kairam, S. (2012). A knowledge-tracing model of learning from a social tagging system. *User Modeling and User-Adapted Interaction*. https://doi.org/10.1007/s11257-012-9132-1.
Resnick, P., & Varian, H. R. (1997). Recommender systems. *Communications of the ACM*. https://doi.org/10.1145/245108.245121.
Ricci, F., Rokach, L., & Shapira, B. (2011). Introduction to recommender systems handbook. *Recommender Systems Handbook*. https://doi.org/10.1007/978-0-387-85820-3_1.
Santos, O. C., & Boticario, J. G. (2008). Intelligent support for inclusive eLearning. *Proceedings - 2008 IEEE/WIC/ACM international conference on web intelligence and intelligent agent technology - workshops, WI-IAT workshops 2008* (pp. 361–364). . https://doi.org/10.1109/WIIAT.2008.372.
Schafer, J. B., Konstan, J., & Riedl, J. (2001). E-commerce recommendation applications. *Applications of Data Mining to Electronic,* 115–153. https://doi.org/10.1007/978-1-4615-1627-9_6.
Šimić, G., & Devedžić, V. (2003). Building an intelligent system using modern Internet technologies. *Expert Systems with Applications, 25*, 231–246. https://doi.org/10.1016/S0957-4174(03)00049-6.
Tang, T. Y., & McCalla, G. (2005). Smart recommendation for an evolving e-learning system: Architecture and experiment. *International Journal on Elearning, 4*(1), 105.
Treude, C., & Storey, M. A. (2012). Work item tagging: Communicating concerns in collaborative software development. *IEEE Transactions on Software Engineering, 38*(1), 19–34. https://doi.org/10.1109/TSE.2010.91.
Tso-sutter, K. H. L., Marinho, L. B., & Schmidt-thieme, L. (2008). Tag-aware recommender systems by fusion of collaborative filtering algorithms. *Search,* 1995–1999. https://doi.org/10.1145/1363686.1364171.
Vander Wal, T. (2005). *Folksonomy definition and wikipedia.* Retrieved November, 16, 2005.
Verpoorten, D., Chatti, M. A., Westera, W., & Specht, M. (2010). Using the personal learning environment manager in a secondary-school lesson. In C. A. Shoniregun, & G. A. Akmayeva (Eds.). *Proceedings of the London international conference on education (LICE-2010) (pp. 197–203)* (pp. 197–203). London, United Kingdom: LICE.
Vesin, B., Ivanovic, M., Budimac, Z., & Pribela, I. (2008). Mile-multifunctional integrated learning environment. *e-Learning* (pp. 104–108). .
Vesin, B., Ivanović, M., Klašnja-Milićević, A., & Budimac, Z. (2011). Rule-based reasoning for building learner model in programming tutoring system. *Lecture notes in computer science (including subseries lecture notes in artificial intelligence and lecture notes in bioinformatics): Vol. 7048*, (pp. 154–163). . LNCS https://doi.org/10.1007/978-3-642-25813-8_17.
Vesin, B., Klašnja-Milićević, A., & Ivanović, M. (2016). Protus 2.1: Applying collaborative tagging for providing recommendation in programming tutoring system. In D. K. W. Chiu, I. Marenzi, U. Nanni, M. Spaniol, & M. Temperini (Eds.). *Advances in web-based learning – ICWL 2016: 15th international conference, Rome, Italy, October 26–29, 2016, proceedings* (pp. 236–245). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-319-47440-3_26.
Wu, S., Ghenniwa, H., Zhang, Y., & Shen, W. (2006). Personal assistant agents for collaborative design environments. *Computers in Industry, 57*(8–9), 732–739. https://doi.org/10.1016/j.compind.2006.04.010.
Wu, W. H., Wu, Y. C. J., Chen, C. Y., Kao, H. Y., Lin, C. H., & Huang, S. H. (2012). Review of trends from mobile learning studies: A meta-analysis. *Computers and Education*. https://doi.org/10.1016/j.compedu.2012.03.016.
Zervas, P., & Sampson, D. G. (2014). The effect of users' tagging motivation on the enlargement of digital educational resources metadata. *Computers in Human Behavior, 32*, 295–300. https://doi.org/10.1016/j.chb.2013.06.026.