Content Assistance and Recommendations in Learning Material
A Folksonomy-based Approach

Benedikt Engelbert[1], Karsten Morisse[1] and Oliver Vornberger[2]
[1]*Faculty of Eng. and Computer Science, University of Applied Sciences Osnabrueck, Albrechtstr. 30, Osnabrueck, Germany*
[2]*Department of Mathematics and Computer Science, University of Osnabrueck, Albrechtstr. 28, Osnabrueck, Germany*

Keywords: Social Tagging, Recommender System, Learning Material.

Abstract: With the variety of Learning Materials (LM) available in Learning Management Systems and the Internet, the time a student requires to select the most appropriate content increases. Especially the use of the Internet to find new LM is time consuming and not necessarily successful. A study accomplished at our university shows, that students mainly look for alternative explanations, content related exercises and examples, which can be used in addition to the existing LM. In this paper we describe the System Learning Assistance Osnabrueck (LAOs), which is based on a collaborative tagging approach with the main goals to give content related assistance for available LM, but also recommend content in further LM e.g. from the Internet.

1 INTRODUCTION

In former times Learning Material (LM) at universities covered usually lecture notes and references to the library where further literature was provided. In the information age the situation is clearly different. The distribution of LM is comfortable, since most universities provide a Learning Management System. Students can access digital lecture notes easily. Moreover the type of LM is more manifold e.g. multimedia content like lecture recordings or YouTube videos enrich the classical lecture notes. Furthermore, the Internet expands the available sources to countless. Many websites provide open educational resources (OER: under CC or GPL licence) or other LM (without any licence) for free. For instance using the engine Google to search for "algorithms" one will find within the first results various lecture notes, books, and videos available for free, but also links to other websites with further LM and OER. A study conducted in a computer science course at our university shows that most of the students invest time to find additional OER or LM on the Internet. Nevertheless, he or she perceives the provided lecture notes within the course as the major material to study with (Engelbert et al. 2013). Another result was, that the quality of the provided LM within the course plays only a minor part and no matter what, students search for additional LM to extend or complement given LM with new examples, alternative explanations and exercises. At this point we see the demand to enrich given LM with additional information and content-related connections to new LM or OER, to increase the students proper use and understanding for the major material. Further, we see a demand to simplify the process of searching for additional material. It has been shown that a huge amount of data and information can lead to disorganization and mental overload cp. (Agrawal et al. 2015). To overcome this we developed a system called *Learning Assistance Osnabrueck (LAOs)*, which provides a process to enrich genuine LM like text documents or video material by a collaborative tagging approach. The system takes advantage of tags in an adapted folksonomy structure to subdivide LM into related content areas. Those content areas can be enriched by assistance information or can be connected to other LM. The pedagogical use of tags to find or discuss context in LM has been considered as a proved method in several e-Learning scenarios (Fu et al. 2007; Luo & Pang 2010). In the next section we describe related work. In Section 3 the concept and implementation of LAOs is described. We will work out the goals of the system more clearly and explain how these goals can be obtained. A formal model to find related content areas in LM and to calculate a rating within the recommendation process is described in Section 4. We finish with results of a first evaluation and a discussion of the

Engelbert, B., Morisse, K. and Vornberger, O.
Content Assistance and Recommendations in Learning Material - A Folksonomy-based Approach.
In *Proceedings of the 8th International Conference on Computer Supported Education (CSEDU 2016) - Volume 1*, pages 456-463
ISBN: 978-989-758-179-3

given approach and demonstrate further benefits of the system.

2 RELATED WORK

Our work is related to several topics in the area of Educational Data Mining (EDM), Recommender Systems (RS) and Learning Analytics (LA), but also to the topic of Social Tagging Systems (STS). In 2.1 we'll give an overview for related work in the fields of EDM, RS and LA under name of Recommender Systems. We'll discuss the topic STS in section 2.2 separately.

2.1 Recommender Systems

RS in general are software tools and techniques providing suggestions for items to be of interest for a user (Ricci et al. 2011). RS are also common in the area of e-Learning and is such an important topic, where hundreds of papers have been published (Manouselis et al. 2013). Dealing with content-related recommendations or assistance is a smaller domain. Possible approaches vary strongly regarding to its aims and techniques, which have various pros and cons. We will briefly discuss those approaches related to ours. Similar to our approach is the idea of recommending Learning Objects (LO), where a LO is the smallest reasonable learning unit. LOs can be recommended on the basis of a user profile, where the user profile contains the current state of students knowledge (Singh & Khanna 2014). LOs are convenient to cover a certain context and can be properly assigned to a current state of students learning progress. Therefore recommendation can be generated rather easily. The main disadvantage of LOs is the necessary amount of metadata to make LOs recommendable (Niemann 2015). Lecturers may not invest the time to generate them. There are several articles that apply the use of tags in a RS for learning. In (Mohsin 2010; Yu & Li 2009) systems are presented where students can add tags to websites or LM to describe them more precisely. In (Mohsin 2010) the tags are used in the recommendation process to find similar websites to study with. The approach in (Yu & Li 2009) takes advantage of tags to help students organizing documents. (Broisin et al. 2010) presents another tag-based system to recommend websites. The approach analyses the tag activities of users and tries to find similar user groups within the system. On this basis the system can derive website recommendation within a user group. The systems in (Mohsin 2010; Yu & Li 2009; Broisin et al. 2010) maintain the approach to describe LM on the basis of tags more precisely. The main downside of those systems is that the tags refer to an entire document and specific content within a document cannot be recommended. The work in (Purwitasari et al. 2011) however focuses on the idea that students can add tags to a specific content within a single document, where the system provides tag recommendations to help students to find the correct context. Thus the system recommendations contain context related information, but cannot recommend the content itself. In (Machardy & Pardos 2015) a framework to evaluate the relevance of video resources in MOOC scenarios is presented. The authors consider the use of Bayesian Knowledge Tracing (BKT) to trace user behaviour and derive resource relevance. The use of implicit behaviour tracking is a reasonable method and is also considered in our work. However the approach is suitable for smaller learning resources like LOs. To recommend resources in dependency of a learning path is another common approach (Pan & Hawryszkiewycz 2004). The idea is to design a learning path depending on a course curriculum and connect the learning path to suitable LM. Related to the problem mentioned for LOs already, preparation time to construct a learning path is time consuming for the teacher. An entirely semantic approach can be found in (Heim et al. 2009), where the system finds similarities in text based resources. Therefore multimedia documents like audio or video documents cannot be considered.

2.2 Social Tagging System

In Social Tagging Systems (STS) users can add freely chosen tags to categorize resources. A folksonomy is the underlying structure of a STS and describes the users, tags, and resources, and the user-based assignment of tags to resources (Hotho, R Jäschke, et al. 2006). We see the mapping of users, tags and resources in a folksonomy as the most promising structure to derive the information we need to reach our objectives (cp. Section 3.1). The work from Hotho & Jäschke reflects the idea, that a resource tagged by important users gets important itself. The main goals are to search for resources, but also to apply a ranking which of the resources are the most important ones. For folksonomies there has been made some research to the use in e-Learning scenarios. The system in (Dahl & Vossen 2008) makes use of a folksonomy in a metadata repository to easily navigate between learning resources. A similar approach is presented in (Anjorin et al.

2011). On the basis of a folksonomy structure the systems predicts a ranked list of important resources.

STS have been established to make a user-based classification of resources and therefore seems a promising technique to categorize not just resources but also content within resources. We see a lack to combine RS with a folksonomy structure to make content related recommendations and give content related assistance in LM. In Section 3 we will describe such a system, however we modified the common use of a STS with it's free shaped tags to a more restrictive approach.

3 SYSTEM GOALS AND OVERVIEW

In the upcoming section we describe the concept of LAOs. First, we will work out the main goals of the systems and how they can be fulfilled, before we give an overview of the system implementation in the second part of the section.

3.1 Goals and Requirements

In Section 1 we already stated the problems students could have when using different LMs. We see the right selection and the sufficient examination of LM as the main difficulties for students. Reasons for this are the huge amount and the variety of LM and OER, which can be accessed on the Internet. The limited time a student spends to examine new material is another main issue. Therefore, we consider the following goals to help students to get a better understanding for LM:

- Find content, which is important in the current state of learning,
- Provide content related assistance,
- Recommend content related additional LM or OER, to reduce the time a student spends to search for it.

We further consider the following goals to give lecturers the possibility to analyse how students use LM and obtain students feedback on LM content:

- Present content, students have issues to learn with,
- Present content, which is appropriate for the students,
- Present statistics on how students uses LM,
- Present LM, which has been used additionally.

To fulfil these goals we propose the use of a collaborative tagging approach, where users can add tags (metadata) to any content within the LM. The user-generated tags can be seen as an explicit user feedback to express a student's opinion on certain content. In addition we provide implicit user feedback, which can be derived from the user's behaviour (e.g. how long a student used a particular LM). The implicit feedback helps to generate LM statistics and to calculate the relevance of the LM. In section 3.2 we will present both types of user feedback more precisely. The tag-based approach leads to the advantage that complex content like lecture notes or multimedia content can be evaluated properly. Since tagging based approaches has been successfully used to classify entire documents, the technique seems to be promising for a content related classification cp. (Broisin et al. 2010). We further assume that the collective intelligence of a user group helps to identify difficulties or utilities within LM. The assumption is that if a single student perceives a LM content to be difficult, important or helpful others may perceive the same.

3.2 System Implementation

The system can be divided into a *tagging*- and an *analysing*-component. The tagging component mainly implements the user interface of the system. The analysing component covers the data analyses and recommendation process. For the recommendation process we implemented a method to extract and rate content from LM. We will give a detailed explanation of the analysing component in section 4.The tagging component provides a web-based tagging feature for text and slide documents, but also for multimedia documents like video files. As stated in section 3.1, we distinguish between explicit and implicit user feedback. In the following we denote the user feedback as explicit and implicit tags respectively. With explicit tags, users can classify LM content according to their opinion by an explicit user statement. For this we implemented several tagging features like comment-, rating- or marker-tools. Furthermore, users can add new LM or OER to the system or can create an explicit connection between two content sections. Implicit tags can be derived from the user behaviour. Implicit tags help to find important sections in LM, which we will call *content relevance* (see section 4.1.2). Moreover, we make use of implicit tags to create implicit content connections (cp. section 4.3). An overview of all available system tags is presented in Table 1.

Table 1: System Tag Overview. E=Explicit, I=Implicit.

Tag	Description
Pre-defined Text Comment (E)	Pre-defined Text Comment (9x positives, 9x negatives)
Quick Tag (E)	Thumbs up/down from a category: Importance, Usefulness, Understanding, Difficulty
Rating (E)	General Rating between 1 and 5 Stars
New Material (E)	Add a new Material e.g. from the Internet
Material Connection (E)	Content related Connection within the same LM or between two different LM within the system
Marker (E)	Marker to mark Content Areas
Page Hop (I)	Jump between Pages in a Text Document
Timeline Hop (I)	Jump on Timeline in a time-based Document (e.g. Video)
Material Hop (I)	Jump between Materials
Residence Time (I)	Time a user spend in a certain area of a LM (e.g. text page)
Use Flag (I)	Increments the count of LM uses

Different to other tag-based approaches, our system provides a fixed set of *explicit* tag types. It is therefore not foreseen for the user to define individual tags. However, it is necessary that the system can interpret the content of a tag properly. This would be more difficult if user's degree of freedom is too high. Furthermore, students are more encouraged to use tags, if there is a set of pre-defined tags available e.g. (Fu et al. 2007). Technically tags hold a pre-defined non-integer value between +1 and -1 (tag score). Tags with a value of +1 indicate a total positive statement; tags with -1 indicate a total negative statement. According to the clarity of a statement, the tag holds a higher (or lower) value (e.g. "The content at this position is important for the current assignment" (+0,9); "The content at this position is vague" (-0,5)). Furthermore, every user is assigned to a non-integer value between +1 and 0, which we call *user score*. A user score depends on how the tags of a user fit into the amount of tags of a whole group. Since the system provides an assessment feature, we also consider adjusting the user score on the basis of taken assignments. Both – the tag and user score – are used to evaluate and classify content in LM. Therefore, users with a higher user score obtain a higher impact when adding tags to content. We denote the clustering of tags, which reveals to certain LM content as *content resources*. More precisely the LM is the resource where users assign tags to and based on the set of tags, the LM will be divided into content-related resources or *sub-resources*. Figure 1 reflects the idea of how the relation between users (u) and tags (t) and their values affect the importance of (sub-) resources (r). To simplify the idea, the figure shows three identical tags on two sub-resources assigned by four different users. The size of the circles corresponds to the respective user-score, tag-score and resource values.

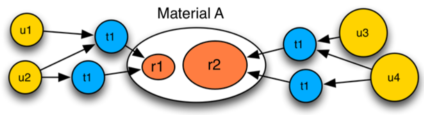

Figure 1: System Implementation Overview.

Figure 1 shows how the value of a sub-resource relates to a user-score and a tag-score. As already stated, sub-resources within LAOs are a content extract or area from a LM. For example it can be a paragraph in a text document or a timeline section in a time-based media. To make content extractable, each tag holds a *multimedia coordinate*, which can vary between the different types of LM. In a text document the coordinate is mapped to X- and Y-coordinates on a text page. In time-based LM (e.g. Video) the coordinate is represented as a timestamp.

4 EXTRACT AND RATE RESOURCES

Section 3 reflects the system concept and implementation. We proposed the main idea and defined scores for users and tags. We further stated how the relation between user-scores, tag-scores and resources work out. Due to this, we propose in the following the method to extract content resources from a LM or an OER for a given set of tags. Further, we present a formal definition to calculate a rating for such resources to make it recommendable.

4.1 Extracting Resources

As stated in section 3.2 we extract content from a LM or an OER by clustering tags. We denote a LM or an OER as a *resource* and a clustered set of tags as a *sub-resource*. To do so, we make use of the multimedia coordinates defined in section 3.2. Overall there are three steps required, which we will introduce in the following section.

4.1.1 Step 1: Clustering Tags

In the first step we cluster tags to temporary sub-resources. For this, we consider an ascending ordered set of tags according to their multimedia coordinate. In text documents we certainly order according to the Y-coordinate. Figure 2 (left side) illustrates a set of tags in a text document. At first, we calculate the distances between two tags whose multimedia coordinates are immediately consecutive. With all the distances between tags we calculate a mean distance with

$$\text{Mean Distance} = \frac{\sum \text{Distances between Tags}}{\text{Number of Tags}} \quad (1)$$

We define two tags as *neighboured* if the distance between both tags is less than the mean distance. Beginning with the first tag in the ordered set, we validate if the upcoming two tags are neighboured to each other. As long as the tags are neighboured, they can be clustered to a temporary sub-resource. If two tags are not neighboured, the clustering for the current temporary sub-resource is completed. The approach is illustrated in Figure 2 (right side).

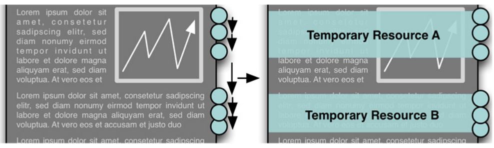

Figure 2: Clustering Neighboured Tags.

4.1.2 Step 2: Validate Sub-resources

Now in step 2 we have to validate the relevance of the temporary sub-resources. First we check if the amount of clustered tags for a sub-resource is big enough. For our model, the condition in equation 2 needs to be satisfied

$$\text{Number of Tags for a temp. Sub-Resource} \geq \frac{\text{Number of all Tags}}{\text{Number of all temporary Sub-Resource}} \quad (2)$$

Afterwards we need to examine if the sub-resource is in a *relevant* area, where an area is part of a LM or an OER e.g. a text page. We denote an area as *relevant* if the *residence time* (the time all users spend in this area derived from implicit tag) and the *tag appearance* (all tags in this area derived from all explicit tags) exceeds the respective mean-score with

$$\text{Residence Time Mean} = \frac{\sum \text{Residence Time of each LM area}}{\text{Number of all LM areas}} \quad (3)$$

$$\text{Tag Appearance Mean} = \frac{\sum \text{Tags of each LM area}}{\text{Number of all LM areas}} \quad (4)$$

4.1.3 Step 3: Clustering Sub-resources

The third step is to investigate if two sub-resources can be clustered again. This can be done if sub-resources are close enough according to their multimedia coordinates. Clustering two sub-resources basically means to merge both respective tag sets. Similar to step one, we first determine the distance between all available sub-resources in a certain area. For this, we use the upper/lower tag coordinate of the respective sub-resource. Using the mean distance score for all sub-resources with

$$\text{Resource Mean Distance} = \frac{\sum \text{Distance between Sub-Resources}}{\text{Number of all Sub-Resources}} \quad (5)$$

we examine if two sub-resources can be merged to a single one. After the third step the sub-resources are finalized and can be classified. This process will be described in the upcoming section 4.2.

4.2 Calculate Resource Score

In section 3.2 we already described the relation between users, tags and (sub)-resources. In the classifying step we now make use of this approach. For this, we switch to a more formal description. Let users U, tags T and sub-resources R are finite sets, whose elements are called users (u), tags (t) and sub-resources (r). Let $Y_\Delta \subseteq U \times T \times R$ be a relation defined by

$$Y_\Delta = \{(u,t,r) | u \in U, t \in T, r \in R, \text{ user u assigned tag t to sub-resource r at time } \Delta\} \quad (6)$$

For simplicity we assume that Y_Δ will always be considered in the current system state so that we use the simplified notation Y for the cumulative Y_Δ. We consider the function $S_U: U \to [0;1]$ to determine the user-score for user $u \in U$. Further, we consider the function $S_T: T \to [-1;1]$ to determine the tag score for any $t \in T$. Let $r \in R$ be a sub-resource in the system. We use a matrix notation to map the relation between a sub-resource r and the elements of the sets U and T. So let A_r be

$$A_r = (a_{m,n}) = \begin{pmatrix} a_{1,1} & \cdots & a_{1,n} \\ \vdots & \ddots & \vdots \\ a_{m,1} & \cdots & a_{m,n} \end{pmatrix}, \text{ with } 1 \leq m \leq |U|, 1 \leq n \leq |T|, \text{ where } a_{m,n} = |\{(u_i, t_j, r) \in Y | \exists r \in R\}| \quad (7)$$

is the number of tags t_j assigned by user u_i to a sub-resource r. Let S_R be a function $S_R: R \to [-1;1]$ to determine a score value of a sub-resource $r \in R$ which describes a positive or negative statement strength of a sub-resource defined by

$$S_R(r) = \frac{\sum_{i=1}^{|U|} \sum_{i=j}^{|T|} \left(S_U(u_i) * S_T(t_j) \right) * a_{i,j}}{\sum_{i=1}^{|U|} \sum_{i=j}^{|T|} \left(S_U(u_i) \right) * a_{i,j}} \quad (8)$$

4.3 Making Predictions

In section 4.1 we described the extraction process for sub-resources in LM or OER and in 4.2 we presented a model to calculate the resource score for any extracted sub-resource. In the following section we will describe how the extracted resources and the respective score can be used to present additional information in LM. This will be done separately for students and lecturers.

4.3.1 Students

As stated in section 4.2 the resource score of $S_R(r)$ for any sub-resource $r \in R$ holds a non-integer value within [-1,+1]. According to a positive or negative statement, the function $S_R(r)$ yields a higher positive resp. negative value. With the tag context assigned to the sub-resource, it is possible to derive an assistance statement for any sub-resource and the related content. Therefore, students get information for relevant content, which can be used to prove their existing knowledge. Figure 3 shows an example of a difficult content within the system. Furthermore, sub-resources will be connected to new LM or OER, which has been added to the system by the user group. E.g. difficult content can be complemented with LM that helped other students already (cp. example in Figure 3). Additionally, the system adds content related connection between the LM or OER, which is already available in the system.

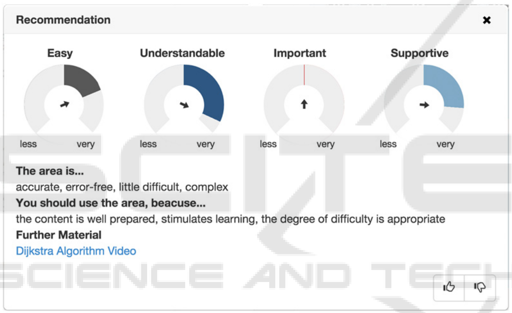

Figure 3: Content Information in LAOs.

This is possible by using the explicit *material connection* tags from the user group. Further the system can derive implicit material connections whilst analysing the material usage of each user. In Figure 4 the material use over the time is shown. Each colour presents another LM or OER.

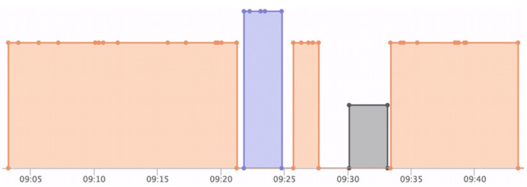

Figure 4: Material Use over the time.

With the switch between two LM and the related tag context, an implicit material link can be derived. The recommendation process covers mainly the notification of the extracted and rated sub-resources. This is necessary if, a student made a contrary statement, a student stated content as difficult (both with explicit feedback), a student did not use certain LM content or a student seems to be confused (both with implicit feedback).

4.3.2 Lecturers

From the lecturers point of view the system gives basically an overview on the students' activities. There are several benefits that come along. Firstly, lecturers get information about how students access given LM or OER. Among statistics how often and how long they used the different LM, the lecturer has access to the detailed user behaviour mentioned in Figure 4. With the using behaviour it is possible to trace back the students' activities and to derive possible weaknesses. It is worth mentioning that the user's information is anonymous. Certainly the lecturer has access to all extracted sub-resources and calculated statements. Therefore, he or she can judge how good or bad the student group can work with the LM. There is also the possibility to access the new LM and the explicit LM connections, which have been added by the students. This helps to review, which LM is used by the students additionally and to review if the students find correct context between various LM.

5 EVALUATION

In the following we describe a first evaluation setting, which has been used to collect data for recommendation purposes. A proper data collection is necessary to show the functionality of the approach presented in section 4 initially. To do so, we set up LM from Algorithms & Datastructures, a classical course within computer science programs, and 35 students are requested to solve problems out of that area. An exercise sheet with 20 exercises has been presented. The exercises covered five different topic areas, where the difficulty level ranged between easy and slightly difficult. In the exercises we asked for factual knowledge, however the students had to solve algorithmic problems. The exercises were prepared with the help of an algorithms lecturer. It was a conscious decision to present exercises from different topic areas in different difficulty levels for various question types. Students should work in different areas of the material to ensure a distributed data collection. Thus we are able to make a qualified statement about the implemented approach. Among lecture notes from algorithm class, we provided an algorithm book and for each topic area one video with the length of 5-15 minutes. The students were allowed to use the Internet. Nevertheless, it was a requirement to add the used additional LM to the system. We accomplished the study in a computer lab with a time limitation of 90 minutes. Each student worked alone on the exercises. All together the 35 students worked 2218 minutes with the given LM. We received 847 explicit and 7104 implicit tags. 43 new LM were added to the system. The first outcome, which seems to be evident, is the significance of the lecture notes. With 1600 minutes students used the lecture notes clearly the most. Certainly we motivated this behaviour in section 1 already. On average the videos were used just 32 minutes. This is mainly because of the length of the videos. Only the provided book was barely noticed. In form of an expert analysis we evaluated the outcome of the system. It is conspicuous that the system was able to work out relevant content. For each content area sufficiently large set of information had been extracted. The extracted content was necessary to solve the exercises properly. This applies for the lecture notes and the videos. In the book the system extracted some useful information, which has been seen as an addition anyway. Especially for the more difficult exercises the negative statements become more frequent. However, the additional LM becomes more frequent equally. This is not surprising, since students are looking for easy or alternative explanations cp. (Engelbert et al. 2013). With the given results the functionality of the system seems promising to achieve the goals proposed in section 3. Especially the extraction of useful or difficult content is working well. Also the number of added LM is high and adequate enough to enrich the given LM. In a second evaluation step in summer 2016 we will verify if students resemble the same. For this, we will ask students to evaluate the extracted content and further LM according to the proposed exercises.

6 CONCLUSIONS

In this paper we presented the system LAOs. The main goal is to assist students in the use and retrieval of LM or OER. We described an approach on the basis of user assigned tags in LM and the analysis of the gathered information. Furthermore, we described a first evaluation setting, which was intended for collecting data. With an expert analysis we were able to approve the proper functionality of the system. The system extracts content according to given exercises in a useful manner. Also the implemented functionality for lecturers to analyse the student's use with LM satisfies the expectations. We assume that the functionality will support lecturers in getting a better understanding for the student's needs and weaknesses regarding to LM. Nevertheless, it is necessary to show the usefulness of the system outcome. This has to be proved in an upcoming evaluation, which focuses on the validation for recommendations from the student's point of view.

REFERENCES

Agrawal, A., Leonard, S. & Paepcke, A., 2015. YouEDU : Addressing Confusion in MOOC Discussion Forums by Recommending Instructional Video Clips. In *Proceedings of the 8th International Conference on Educational Data Mining*. pp. 297–304.

Anjorin, M., Rensing, C. & Steinmetz, R., 2011. Towards ranking in folksonomies for personalized recommender systems in e-learning. *CEUR Workshop Proceedings*, 781(October), pp.22–25.

Broisin, J. et al., 2010. A personalized recommendation framework based on cam and document annotations. *Procedia Computer Science 1*, 1(2), pp.2839–2848.

Dahl, D. & Vossen, G., 2008. Evolution of learning folksonomies: social tagging in e-learning repositories. *International Journal of Technology Enhanced Learning*, 1(1/2), p.35.

Engelbert, B., Morisse, K. & Vornberger, O., 2013. Zwischen Nutzung und Nutzen – Die Suche nach geeigneten Lernmaterialien und deren Mehrwerte im Kontext einer Informatikveranstaltung. In *GMW 2014 - Lernräume gestalten - Bildungskontexte vielfältig denken*. Zürich, pp. 508–519.

Fu, X. et al., 2007. Video Annotation in a Learning Environment. *Proceedings of the American Society for Information Science and Technology*, 43(1), pp.1–22.

Heim, P. et al., 2009. Semantisch unterstütze Informationsextraktion aus Dokumentenmengen. *Hartmut Wandke; Saskia Kain & Doreen Struve, ed., "Mensch und Computer 2009"*, pp.415–418.

Hotho, A., Jäschke, R., et al., 2006. Folkrank: A ranking algorithm for folksonomies. *Proc. FGIR*, pp.2–5.

Luo, G. & Pang, Y., 2010. Video annotation for enhancing blended learning of physical education. *Artificial Intelligence and Education (ICAIE), …*, pp.761–764.

Machardy, Z. & Pardos, Z.A., 2015. Evaluating The Relevance of Educational Videos using BKT and Big Data. In *Proceedings of the 8th International Conference on Educational Data Mining*. pp. 424–427.

Manouselis, N. et al., 2013. *Recommender Systems for Learning*, New York, NY: Springer New York.

Mohsin, S.F., 2010. Web based Multimedia Recommendation System for e-Learning Website.

Journal of Advanced Networking and Applications, 223, pp.217–223.

Niemann, K., 2015. Increasing the accessibility of learning objects by automatic tagging. *Proceedings of the Fifth International Conference on Learning Analytics And Knowledge - LAK '15*, pp.414–415.

Pan, W. & Hawryszkiewycz, I., 2004. A method of defining learning processes. *Beyond the 21st ASCILITE Conference*, pp.734–742.

Purwitasari, D. et al., 2011. Ontology-based annotation recommender for learning material using contextual analysis. In *Proceedings of the IETEC'11 Conference*. Kuala Lumpur, Malaysia.

Ricci, F. et al., 2011. Recommender Systems Handbook. In F. Ricci et al., eds. *Recommender Systems Handbook*. Boston, MA: Springer US.

Singh, T. & Khanna, S., 2014. Reinforcement learning approach towards effective content recommendation in MOOC environments 1. In *IEEE International Conference on MOOC, Innovation and Technology in Education (MITE), 2014*. pp. 285–289.

Yu, L. & Li, Q., 2009. Personal Media Data Organization and Retrieval in e-Learning : A Collaborative Tagging Based Approach. *MTDL*, pp.1–7.