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A Survey on Automatically Annotating Learning Objects with Competence Leveling

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ABSTRACT

Online learning is becoming an essential part of educational institutes. Educational institutes apply competence in order to know the ability or skill of students. Many educational resources are available online. The learning objects enriched with competence information supports the learners for retrieving the relevant resource. The non-annotated learning objects pose a challenge for efficiently accessing and retrieving the learning resources by the users; that is the cold-start problem. To address this problem, learning resources are automatically annotated by automatic tag annotation method which is known as α-tagging LDA method, i.e. Latent Dirichlet Allocation which is based on a probabilistic topic model. The competence levels which are annotated to learning objects by experts in the subjects of their interest is a time consuming process. Therefore the learning resources which are available online could not enclose competence information due to this problem. This survey studies how educational resources are assigned automatically with competence levels, the approaches are: first facilitate competence assignment task by experts and second: supporting the learners to search and retrieve proper leveled material. The main focus of this survey is to enrich learning resources with competence, which provides the learners in identifying the effective resources which make the learners reach their target competence.

Keywords:- Metadata generation, cold-start, LDA, Competences, Automatic Competence Classification

I. INTRODUCTION

Now-a-days many people are adapting to learn and work through online process; they can communicate in various ways as the information processing speed is increasing day-by-day. Gradually learning process is becoming a web-based activity collaboratively [2] than a one which is solitaire. Learning on online is being adapted by the educational system. Collaborative learning system consists of a digital collection of learning objects (Los) like lecture notes, presentations and lecture videos which are available in online repositories [27]. Therefore the learners can search for a specifically related learning resource on online and enrich it with some value.

The process of enriching the learning objects in a collaborative system is a difficult task, so the users can browse the related resources on the online using the tags. The tag which is provided by system effectively covers the resources on the online system; then users can browse the relevant learning resources in an effective manner. If the tags are not provided in a clear manner then the user cannot browse the specific resource efficiently on the online system.

Tags are provided only for a small part of resources, and other resources are not linked metadata. Whenever new resources are added to the repository without tagging the related learning objects cannot be traced out easily, this problem is addressed as new item cold-start problem [27]. Automatic tagging approach is considered for this problem which provides tags for untagged learning objects.

In this approach set of keywords i.e. tags are considered and a new resource which is untagged can be related to known document by considering the set of tags that approximately relate to that document. For automatically associating tag for untagged learning objects [27] α-Tagging LDA method which is based on the probabilistic topic model Latent Dirichlet Allocation [4] is used.

Learning objects are to be understood by the users. To measure the understandability of learning objects, metadata competence is performed. A competence is referred as an effective performance performed by a person in his job/domain at different levels of their proficiency [31, 48]. The Competences are applied in learning process; such that a learner's performance and skills can be known. Educational resources which are available on the web are enriched with competence level, which makes learners in identifying a relevant resource in order to reach their competence goals. The process of learning online for teacher and students is made efficient by providing competence for educational resources. Experts' level is also added to the competence information such that the learners can understand the resource and reach their target.Therefore the Eight levels European Qualification Framework (EQF) have been considered that describes a competence, which ranges from the beginners to the experts [48].Learning resources are available freely with Open Archives initiative (OAI).Through the utilization of OAI-PMH protocol[1], many external repository contents are listed by learning environment. The open content strategy suffers from information overloading such that thousands of new resources are added to the library when a new repository is added to it. Therefore it is a difficult task for experts for evaluating the learning objects and assigning the competence to it.

Therefore this paper is mainly focused on for providing a mechanism such that the learners can find the relevant resources and judge the skill of the resource, by understanding it and provide the competence level to the resource. The expertise levels are automatically assigned to LOs with competence by considering a strategy that makes use of knowledge from the collective opinion of group of individual. Thus an attempt is made for building a tool for an automatic competence leveling [48] for the learning objects.

In this survey paper, an attempt is made to present the research advances in automatic competence assignment tool from the last decade by considering the development speed of educational resources and ensure the easy access and understandability of LOs. Section II describes the methods for automatically tagging the learning objects. Section III describes the α-TaggingLDA method. Section IV outlines the importance of competences in the learning process and describes the methods for assigning competences to the learning objects automatically. Section V describes automatically assigning the expertise level to LOs with competence. Section VI describes the conclusions and the results obtained by evaluation and final remarks are described.

II. AUTOMATICALLY TAGGING LEARNING OBJECTS

In order to address the cold-start problem in the collaborative system some methods are followed.

i. Learning objects enrichment
ii. Automatic tagging
iii. Automatically enhancing the learning objects with tags.

A. Learning Object Enrichment

LOs are considered as a modular resource that can use and reuse the data in order to support online learning activities [27]. Therefore LOs acts as a basic element for newly created content. For enriching learning object in collaborative environment, tags are considered to navigate and to associate the resources. The importance of additional metadata for using and reusing the learning resources is provided by Lohmann et al.[13, 27] and also suggested guidelines that follow approaches of automatic tagging. The guidelines that are suggested are (i).Using a set of tags that are stable for describing resources. (ii). Using tagging method i.e. using for recommendation systems with tags. (iii). Using the text which is extracted from the set of keywords. (iv). Using the selected tags for convergence.

[1]http://www.openarchives.org/pmh

Considering the tagging of resources and web2.0 sources, ReMashed [6, 7, 27] focused on cold start problem for new users and showed that the user lack of information for recommender systems that uses already tagged learning resources and also addressed the cold start problem for a new item such that untagged resources can be tagged. Therefore the recommender system improves the performance by tagging the objects [19, 27].

LearnWeb2.0 was introduced by Abel et al. [1, 27] such that the resources can be discovered, shared and managed and provides a platform for learners and course generator. Automatically annotating the resource service is provided for collaborative searching, such that when a searching is performed the result consists the related query terms which are tagged automatically and the relevant information is retrieved from the system based on the query given by the user. Therefore initial user interaction is needed in order to annotate the resource. User interaction is not needed for multimedia resources that are without metadata availability. Therefore user interaction is not needed for this approach which is based on content in order to annotate the LOs automatically.

B. Automatic Tagging

To annotate an LO, various forms of enrichment can be used for tagging a resource, commenting a resource and rating a resource. Tags are used for improving recommendation system [19, 18, 27], and also facilitates searching capabilities [3, 10, 27]. Personalization is been provided by tags and provides personalized information access across different media types [19] and also provides information access improvement in collaborative tag recommendations [16, 27].Annotating automatically and recommending with the tag are methods used for dimensionality reduction that is based on Latent Dirichlet Allocation (LDA) which is a probabilistic topic model and factorization tensor [16, 17, 20, 27]. In order to overcome the cold-start problem Krestel et al.in[11,12] provided a relative set of tags by considering the resources that are annotated by various users.

For automatic tagging, the tags that are assigned previously by users are used to build an LDA model [4, 5]. Therefore resource is provided with a tag from the topics which are discovered with the help of LDA in the system. When a new resource is not annotated, the set of top tags of each topic was used to expand the latent topic.

By considering the performance of above approaches the automatic tagging method provides the assumptions for dense data from which a model has been developed. Diaz-Aviles et al. [5, 27] represent α-TaggingLDA method in order to overcome cold -start problem and in this method the LOs are annotated.

Therefore evaluation process of automatic tagging method provided metadata generation of resources for collaborative learning environment [27].

C. Automatically Enhancing Learning Objects with Tags

Learning objects are enriched by tags using α-TaggingLDA method presented by Diaz-Aviles [5] for tagging the learning objects automatically. The Cold-start problem can be avoided using this method by considering the content of resources which are exploited without collaborative interactions. LDA is Latent Dirichlet allocation [4] used to generate probabilistic model for topics from the corpus of text. Therefore LDA model idea is to consider the resources that are mixed randomly over the topics that are latent and the topics are characterized by the distribution of terms.

LDA model [5,27] considers the collection of a set of text documents D and a set of topics Z such that the topics are distributed within a particular document and probability is considered as p(z|d) and also set of terms are considered so that the probability distribution of terms are provided as p(t|z). Therefore every term is produced by sampling the topics in the document and by distributing the topics. The LDA model provides the distribution of terms in a document as the following equation 1.

$$P(ti \mid d) = \sum_{z} P(ti \mid zi = j)P(zi = j \mid d) \quad \text{…. Eq 1}$$

Where $P(t_i \mid d)$ represents the probability of distribution of terms in a document.

$P(t_i \mid z_i = j)$ represents the term t_i probability with the topic j.

$P(z_i = j \mid d)$ represents the probability of sampling the jth topic by the ith term in a document.

And $|Z|$ represents the set of topics.

The equation 1 was presented by E.Daiz-Aviles, M.Fisichelta, R, Kawase for auto tagging the unsupervised Learning objects [27].The goal of LDA model is to predict the probability distribution of given topic over terms i.e. (t|z) and distribution of topics over documents i.e. P (z|d). Therefore based on the distribution of Dirichlet which uses Gibbs sampling [8] the distributions are sampled. Thus which topics are necessary for a specific document, and which term is necessary for which topic is indicated.

III .α-TAGGINGLDA METHOD

In α-taggingLDA method, an example is considered where an LO is named with knowledge technologies in a context which is new to the system and it is not annotated with any tags that become difficult for a collaborative system to consider it as a candidate of some particular resources.

The method of α-TaggingLDA is given in figure1 in which the relevant Los with textual content are been extracted first which contains the title, metadata and a document is created which is denoted d_{LO} and an LO with relevant documents is known as ad-hoc corpus which was given as $corpus_{LO.}$ In α-TaggingLDA method similarity measures on learning objects are not restricted to link a corpus with LO. Therefore an evaluation and benefits of automatic tag annotation for the collaborative system is considered [5, 9, 14 27]. In the evaluation process the benefits of automatic tag annotations for a collaborative learning environment are measured [5, 14, 15, 27].

IV. AUTOMATICALLY ASSIGNING COMPETENCE

A. Competence

Competence measures the performance of individual in their specific job/task efficiently [31, 48]. Testing for Competence Rather than for Intelligence [34], published by McClelland proposed that competences analysis of a person is better than testing intelligence. Many educational institutions follow competence process to know the ability of the person. Lindstaedt et al. [33] proposed a prototype which is considered as best example for using the competences practically.

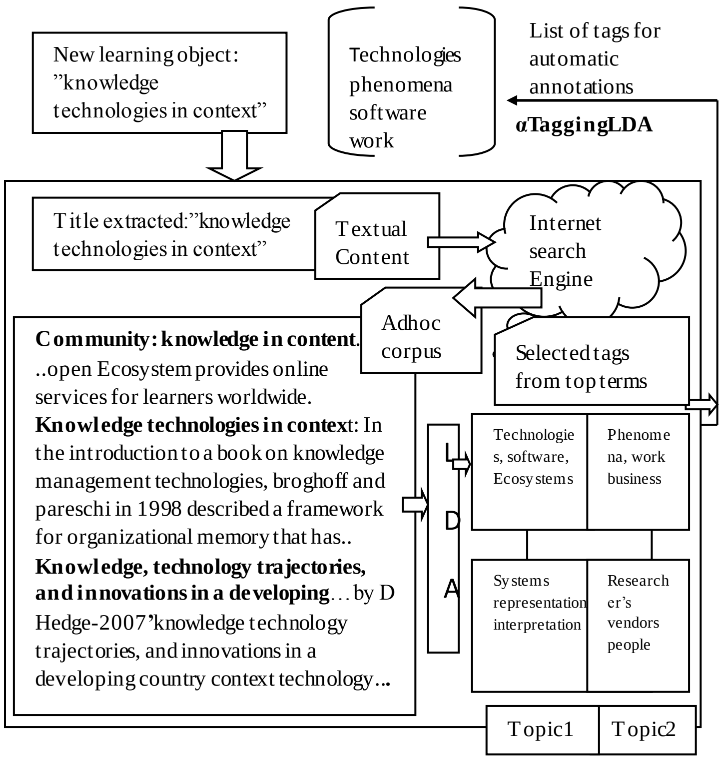

Figure 1: α-*TaggingLDA* method is used where new LO like Knowledge Technologies in Context is annotated with six tags in a list. $TopN_{tags}$(LO) is considered with six tags like {technologies, phenomena, software, work, ecosystems, business} that are based on two LDA topics.

Another example proposed by Habermann et.al [28] identified that the learning process regarding the managers of small-medium enterprise (SMEs) improves if the learning resources on the web are easily found and accessible. These materials are accessible if they could match the competence development needs.

Many authors researched on different strategies for accessing the right educational resources on online in an efficient manner in order to reach the competence target. Many technologies have been developed to support technology enhance learning (TEL) process. Learners can retrieve the resources form different repositories. The process of retrieving educational resources is difficult due to the lack of descriptive metadata, such as competences and skills. The standards of competence-related metadata for educational resources have been proposed in the literature [37, 39].In order to tag the educational resources with competence in a meaningful way, a competence-based application profile was introduced which is IEEE LOM [23, 24, 37, 39]. Competency characteristics relevant to learning resources have been proposed. Therefore it has been analyzed that filling metadata manually is often hard to achieve and laborious task. To deal this problem, Open Scout [15, 39] proposed a collaboration tool for describing its educational resources metadata [29]. Competences and skill metadata can only be changed by authorized persons, such as content providers or facilitators, thus it was analyzed that metadata is not filled out completely [48].

The Importance of visualizing competences and their sub-competences for learning objects was introduced by Auzende et al. [25]. Authors developed software which makes it possible to enter taxonomy [49] with four levels and competence and sub-competences. In this approach, an interface was used such that the teachers can create, classify, upload, search the LOs and also enriching the metadata is performed [25, 48]. Therefore competence levels to the Los were always assigned by humans, and the competence level was refined according to users' feedbacks [48].

Thus once each LOs are assigned with competence, the authors' can update/modify the competence level. By this method Automatic competence classification is not handled [25, 48].

Linking educational resources with competences based on curricula was introduced by Van Assche [23]. In this method, a curriculum is considered at different levels [23, 45]. The curricula are used at teacher levels which pose a plan for a year. An important element of curricula is educational goals. These goals are broken down into targeted competences [23, 43]. Competences have been part of educational research such that growth in importance and the emergence of life-long learning is expected [37, 23, 44].

Mapping process among different curricula is performed such that a resource which is tagged with a particular curriculum is discovered and given with another form of curriculum [23, 45]. A curriculum mapping is described in a way that one curriculum component maps the component of another curriculum which has Boolean expression[23, 46, 47].An approach is provided where teacher tags a resource with their own curriculum such that another teacher finds the resource back with the help of curriculum which is local.

In this approach in order to store the metadata with competences which relate to the curriculum, an IEEE standard is followed for LOM i.e. Learning object metadata [23, 37, 39]. LOM is used to store the competencies where the section 9.1 of LOM indicates classification that concerns a competency and section 9.2 stores the terms which form an action verb multilingual thesaurus [23, 39, 40, 41, 42]. Therefore interoperability is placed between different curricula and an automatic approach is considered to assign competencies to the learning resources such that these LOs can be retrieved efficiently and reused by teachers and students [23, 26, 35, 36, 38].

A flexible competency framework was provided by Melis et al. [35, 36], that provides a competence assignment process automatically.TEL system provides classification of competences in order to react to student actions automatically at a micro level (eg.Feedbacks), and at a macro level (eg. Los) and also a student model were built by processing these reactions. Such classification needs to be reusable and reproducible in order to reuse Los. A framework for competency systems was presented by PISA [38] and Blooms Taxonomy [26] to reuse the Los. This approach is complementary, such that the learning objects are automatically classified based on their level and competence type and therefore the learning object are reused that makes the course generator to take the domain knowledge and competence level[23,25,31,35,36,48].

Using expert's knowledge the resources are elcitiated, modeled and evaluated this approach was presented by Ley et al [32]. A structure of competence performance was constructed by korossy 1997 for integrated learning system. In this method a set of competences are needed to structure with a prerequisite relationship which is "diagnostically relevant", but it constitute a challenge for learning domain that are ill-structured by placing this prerequisite relation on a set of elementary competencies[50].

Ley and Albert introduced task competency matrix such that experts are asked to assign competencies for each task. Identifying feasible states of competences is the idea of this task by interpretation function, such that when a person performs a particular task, he or she is required to have all competencies that determine the minimum interpretation of task [24, 32].

In order to minimize the domain experts efforts a methodology for building and evaluating competence performance structures for work integrated learning has been developed. In order to validate the LOs, a competence-task graph [32] is designed by expert's knowledge that provides high-quality structure for competences, knowledge, skills and tasks.

R.Kawase et.al [31, 39, 48] has focused his work with the Open Scout learning environment[2]. The Open scout portal provides the outcome of an EU co-funded project[3] [48].This project connects European Open Educational Resources (OER) and also integrates its searching method service into existing learning suites [39, 48]. Open scout suffers from the information overloading problem [39, 48], which integrates contents from different repositories and number of learning materials are added daily to the environment without experts annotation for competence levels.

A novel approach was proposed to handle this problem that annotates the learning resources automatically in open scout with competences [5, 15, 27, 31].

The problem involves two distinct steps.

(i). identify the similar competences of a given object.

(ii).identify the expertise level required.

[2]http://learn.openscout.net

[3]http://openscout.net

Los which has a specific competence level [48] provides an efficient searching for learners and teachers, and a management-related approach was developed for competence classification (see Table 1.) in this approach, in order to generate initial competence classification based on experience and literature of academic [27, 31] a group was formed with ten domain experts from higher education, Business schools and SMES. Then a pre-test was conducted by domain experts of high learning institute in order to assess the content of competencies involved, and therefore, the content validity is ensured.

Therefore within the Open Scout project, lists of keywords that are more relevant to each competence are created for competence classification (SeeTable1).

Competences	Relevant keywords
Business and law	Law, legal, contract, litigation, formation, antitrust
Decision sciences	Decision, operation, risk, modeling, forecasting
General management	Milestone, planning, plan, management, evaluation, task, optimization
finance	Financial, banking, finance, capital, cash, funds, flow, debt, value, equity.
Project management	Monitoring, planning, organizing, securing, management, report
Accounting and controlling	Accounting, balance, controlling, budgets, budgeting, bookkeeping
Marketing and sales	Advertisement,marketing,advertising, communication,branding,b2b
Human resource management	Management, resources, employee, resources, training, relation, competence.
Technology and operations management	Ebusiness,technology,egovernment,ecommerce,outsourcing,operation
Organizational behavior and leadership	Leadership, behavior, organizational, team, culture, negotiation.
Entrepreneurship	Entrepreneurs, opportunity, entrepreneurship, start-up, business
Strategy and corporate social responsibility	Society, strategy, responsibility, innovation,, regulation, sustainability
Management information system	Information, system ,management, IT, data, computation, computer

Table 1 shows the competence classification of the Open Scout repository and the examples of most relevant keywords.

The goal of applying competences to LOs is to find and retrieve the relevant resources on online such that learners can judge the skill to understand the materials and reach their target competence.

B. α-TaggingLDA

The author named R Kawase worked on assigning competence annotations automatically for learning objects, a tag-based competence assigning method can be applied to any repository that consists of documents where competences that are involved are known in advance. Therefore a methodology that extracts the tags from the learning objects was involved by assigning the competence. Competence annotation method provides α-Tagging LDA as its extension.

Diaz-Aviles et al. introduced a state-of-the-art LDA- based approach that tags automatically [5, 27, 31]. In order to overcome the new items cold-start problem α-Tagging LDA was designed by exploiting the content resources, without considering the collaborative interactions. Therefore ranked list of representative tags are outputted for a given LO using α-Tagging LDA.

C. Tag-Based Competences

At the top of the tagging automatically method a new layer is added to which a document that involves the probable competence is identified [5, 31]. Classification layer involves two different inputs; (i) It involves a list of keywords that are ranked which describes the resources that are to be classified. (ii) It involves a list of competences where a document consist a list of keywords which describes competence (See Table 1).

Based on these inputs, scores are assigned by classification method when a match is found between the competences and a list of keywords in the document. A linear decay is applied on the matching-score, as the tags of the document are ranked before. It means that a high score is assigned when a competence keyword matches the keywords of the first document. Therefore as the ranking of document keyword are high the low will be the final score. The document is assigned with top competence scoring after the process of matching and the sum of scores of each competence are computed [5, 31].

The algorithm was presented by R.Kawase, P.Siehndel. B.P.Nunes[31] to depict the matching method. Thus all keywords which are present are submitted first to the stemming process.

Algorithm: Pseudo code for the keyword-term matching method.

1. Begin
2. Set of documents is considered
3. For each and every document do
4. A top N α-tagging LDA Keywords are considered
5. For every keyword in the document do
6. keyword Index is incremented, and for each competence do
7. Competence's terms are considered
8. For every competence terms do
9. If keyword is equal to terms then
10. Competence-score+ = 1/keyword Index;
11. Competences scoring are returned.

The evaluation process of this method considers the similarity of learning object and number of assumptions which are believed and validated to check whether an optimum result is produced or not by automatic competence assigning method [21, 22, 31].

The most relevant documents are calculated by considering the most representative 15 words with the help of their TF-IDF values [21], and also a query was generated with the help of these words. Lucene's scoring function was considered for ranking the documents which are based on the Information Retrieval Boolean model and Information Retrieval Vector Space Model [22, 31].

V. COMPETENCE EXPERTISE LEVELING METHOD

Learning object which is annotated with competence information assigns the Competence expertise leveling by the European qualification framework [48] which represents eight levels for describing a competence which ranges from beginners to experts, which is assigning a score for LO with competence between 1 and 8.

The author R kawase worked on Wikipedia repository to automatically assign the competence leveling for learning resources in it. Wikipedia is considered as a largest repository, where text-based articles are created and maintained by persons. For calculating the levels of competence the authorized information of Wikipedia is extracted with the help of link structure. Therefore Wikipedia's article authority is based on the article popularity which is considered as the evidence of its complexity. The more the article is popular; it is easier for the reader to understand. The popularity of an article is based on the number of incoming links [30, 48].

The work was done by considering the snapshot of the dataset of the entire Wikipedia corpus from 2011 October, which contains 4.5 million pages and more and the documents in it are considered without any redirect pages. The statistical information of linked articles and Wikipedia categories list are collected additionally.

Then the automatic level of competence assigning [48] is considered and divided into following steps.

i. First, Using DBpedia Spotlight[4] Web Ser-vice each document is semantically annotated (RDFa).

ii. The content of document which is enriched by DBpedia resources or the Wikipedia articles is returned as output.

iii. To the content of learning object, each link is being added and also a number of incoming links for each article has been checked, i.e. for a Wikipedia article its authority value is queried.

iv. The small dominant article contains more numbers of incoming links (see figure 2); where power law distribution is considered for distribution of authorities.

v. To compensate a logarithmic smoothing function is applied before proper normalization is considered.

By this method, the information is exploited and some of the top authorities' dominance is counter- balanced. Every LO consists of a number of incoming links for each linked article, i.e. it contains the information of authorities' value. The competence level method is applied to only Los which is assigned with single competence [31]. Finally, final level of competence is computed by considering the linear combination of all authorities' values for each and every linked term and normalized them with a scale of European Qualification Framework [23, 30, 48].

A. *Evaluation and Results*

In the process of evaluating the performance of competence leveling, the author considered an open scout dataset which consists of 21,768 learning objects and the data is pruned on English learning objects which consist of 500 characters of minimum length, therefore 1,388 set of documents resulted, and then they considered the resources which had at least 10 terms that are annotated by DBpedia spotlight service. Finally, they assigned 1051 learning objects with competence levels. The resources that are annotated with competences is a time-consuming process which was performed by the experts in the area of their domain. And the results evaluated at the ground truth were very limited. Therefore 100 resources were considered which are annotated with competence by the experts, Out of these 100 resources, 60 resources were considered in English language, and out of the 60 resources 44 resources were considered as clearing all directives of resources, that a document should have at least 500 words and at least 10 terms should be linked with Wikipedia resources.

Open scout included lower and upper boundaries for competence assignment which was needed by the experts and 37 learning objects were resulted as an output, out of 44 learning objects that are considered as ground truth in the evaluation process. Therefore the competence level which was given by experts was assigned automatically within the boundaries. Therefore the result showed that the learning objects in Wikipedia's linking structure are validated by deriving the expert's level which was given to the Lo in order to better understand the Learning objects

To prove the correctness of assigning competence levels to the learning objects and for providing automatic evaluation, the author performed a user evaluation process. They considered 1051 Learning objects that are assigned with competence levels. Out of these 1051 Los they randomly selected 100 LOs, and then they have considered 4 experts from business and management field for evaluating the competence assignments. Each expert was given 25 learning objects with their competence, and asked them to evaluate the competence assignment with 5-point Likert scale rate and finally, the experts agreed with the proposed competence level [48].

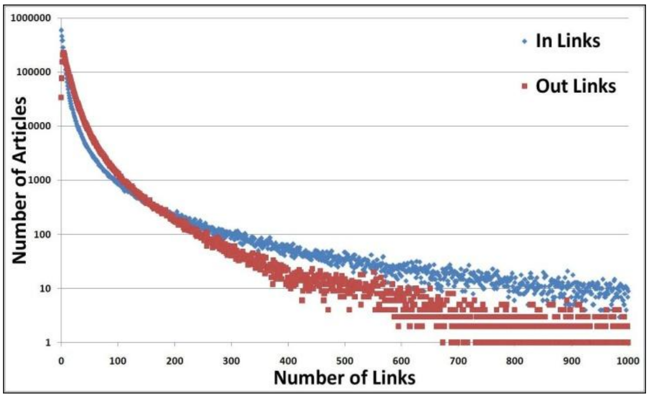

Figure 2. Shows the Distribution of Links in Wikipedia dataset

Courtesy: R kawase,P Siehndel[48]

Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
7%	8%	3%	44%	38%

Table 2: The table shows the result of expert's agreement with assigned competence level.

The results shown in Table 2 gives that the agreed and strongly agreed with 82% of cases for assigning the competence levels automatically to learning object[48].

VI. CONCLUSION

In this paper, we discuss three approaches for automatic competence leveling. In the first approach for automatically annotating Learning objects α-Tagging LDA method was proposed that produces quality metadata enhancement for LO. In this approach metadata was automatically generated and improved the personal recommendations of LOs that overcomes a cold start problem.

In the second approach a methodology was discussed to assign the competences to Los automatically that is based on a tool which is automatic tagging tool. In this approach, the given competence is evaluated through a number of cases that considered LOs text based similarities. The results of this method provide very few occurrences; therefore different competences were assigned to most similar items. In order to enhance the competence for metadata learning object effectively, a coherence and effectiveness of this method were interpreted as evidence.

In third approach, a solution was proposed for predicting the competence level which was involved in the learning object by considering the link structure existing in Wikipedia documents to describe the abstraction levels which are necessary for understanding the documents.

In this approach results showed that automatic competence level assignment achieves an accuracy of 84% and user evaluation with experts achieved 82% of accuracy. These approach such that the collaborative learning environment consists of digital collections of learning materials which are available in online repositories. As education system is an emerging field of research. Many learning materials are made online, therefore many techniques have been discussed in order to retrieve and search for relevant learning resource on online and enable the learners to understand and judge the required skill with the help of competence levels.

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