ISSN: 0975-833X

Available online at http://www.journalcra.com

INTERNATIONAL JOURNAL OF CURRENT RESEARCH

International Journal of Current Research
Vol. 13, Issue, 10, pp.19029-19041, October, 2021

DOI: https://doi.org/10.24941/ijcr.42351.10.2021

RESEARCH ARTICLE

EDUCATIONAL KNOWLEDGE RESOURCES ASSESSMENT USING MACHINE LEARNING & LINKED NETWORKS – PART I

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ARTICLE INFO

Article History:
Received 29th July, 2021
Received in revised form
27th August, 2021
Accepted 15th September, 2021
Published online 30th October, 2021

Key Words:

Digital Resources, Educational Resources, Machine Learning Model, E-learning, Recommender systems.

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ABSTRACT

With the existing challenge in education industry reinforced by theconsistent pandemic situation, adapting the educational resources in order to help to personalize and accelerate the usage of digital content used by teacher is an emerging topic in this sector. New generation of student needs evolving multimedia resources that are easy to use, assemble and personalize, adapted to the subject and time of learningin a digital and mobile world. In addition, the quality and relevancy of resources is one of the key factors to increase the value of education and speed up digital learning for all kind of students. Also, identify the best resources for a specific knowledge domain and educational level is another challenge. Machine Learning could be efficiently used to increase the knowledge assessment for a specific student with the most valuable digital resources. In this paper, we proposed MLM-based educational recommender system (ERS) named EKRAM. The Educational Knowledge Resources Assessment using Machine Learning &linked Networks (Part I), whose objective is to assess content using machine learning models that analyze educational and classification metadata in order to identify the most relevant content and organize them to produce an educational resource for a specific usage in a set of progressive levels. Using simulation prototypes, we tried to demonstrate that EKRAM may improves accuracy and efficiencyof the educational process. This article is the firstpaper of Educatio project using EKRAM.

Citation: Ronald Brisebois and Apollinaire Nadembega. "Educational knowledge resources assessment using machine learning & linked networks – part i*", 2021. International Journal of Current Research, 13, (10), 19029-19041.*

INTRODUCTION

In recent years, there has been significant growth in the use of online learning resources by learners.Artificial intelligence in education typically focuses on identifying what a student does or doesn't know, and then subsequently developing a personalized digital learning resources for each student. It can automate some aspects of the digital learning, create recommendations based on individual learning history and maybe help students to choose future career based on data and process linked to their learning ability. At the same time, upon analyzing student's data, teachers can set the curriculum to match each student's capability and pace of learning and personalized learning possible. Artificial intelligence will continue to fill gaps in learning and teaching and help personalize and streamline education. This big data and analysis of MLM (Machine Learning Model) could be useful for personalized digital learning, determining interventions, and improve tools for education. There are many use cases in term of exam security, identification of cheating during digital exams, AI-powered proctoring to conduct exams without any physical invigilation. MLM can empower to conduct exams without any physical human intervention of the traditional exam process. It can also help performance evaluation of the student or group of students. The analytic information on student exam performance can be analyzed using big data algorithms. It can provide useful insight into student performance and it can help reduce bias from personalized feedback to the students. Several recommender systems (RS)[1-29, 31, 32-37, 39] have been proposed and recorded significant successes. Although conventional recommendation methods such as collaborative filtering and content-based have demonstrated success in domains such as e-commerce, music, movies, images and books, there are still some challenges experienced in attempts to provide accurate and personalized recommendations of learning resources in e-learning arising from differences in learner characteristics, learner contexts and sequential access patterns among the learners;this may explain the fact that current learning management systems such as Moodle and WebCT are systems that provide e-learning material in a fixed-sequence, delivering the same content to learners regardless of their differences in background knowledge.

According to literature, the majority of the learning management system (LMS) only consider three dimensions to an adaptive framework, that is, the learner model, the content model and the adaptation engine. In addition, the majority of the LMS are based on the principles of macro-adaptation which provide a “static” snapshot of a learner's profile instead of dynamically adjusting the adaptation as learner variables. Learner’s contextual information such as knowledge level and learning goals change with time and situations. These contextual changes have an impact on learner preferences for learning resources. Also, different learners have different sequential access patterns for learning resources that can equally influence the learning resources that should be recommended to the learner. In other word, learner characteristics, learner context and sequential access patterns have some influence in determining the learner preferences for a learning resource, hence they should be captured during recommendation. Detecting the learner model offers a potential to recommend a learning material that is adequate to the learner progress. Accordingly, the learning objects and hypermedia can be adapted to each individual student to meet the personalized learning needs. This paper proposes a framework for applying recommender systems in personalized e-learning domain. Furthermore, the recommender system previous examples, opportunities, and associated challenges are discussed [1]. Unfortunately, conventional educational recommendation systems do not incorporate learner model such as learner characteristics, learner context and learner’s sequential access patterns in generating recommendations for the learner. In addition, conventional educational recommendation approaches experience the cold-start and sparsity problems, making them unreliable in e-learning scenarios. Majority of the educational recommendation systems currently in use still face similar challenges due to lack of incorporation of additional learner information in their recommendation processes. Almost any learning management systems (LMS) propose a contents recommender model that may help teachers and educational resources editors to provide best learning resources according to learning goal, learning domain, learning level and learner model.

Few researches have been done in educational or e-learning recommender system [1-11, 25]; in addition, they still experience drawbacks in making accurate recommendations of learning resources in e-learning domain due to differences in learner characteristics such as learning style, knowledge level as well as learners’ sequential learning patterns.For learners engaged in self-study online distance learning, this may result in material being presented at either too high or too low cognitive levels; that may result in either frustration or boredom among learners [5].The main drawback is the fact that existing educational recommender systems focus on the identification of best educational resources for learners instead of to identify the best contents for teachers to create best educational resources according to learning domains, educational objectives, disciplinary competences, educational levels and learner specific characteristics. To the best of our knowledge, the main limits of existing approaches in educational recommender systems (ERS) and learning content management systems (LCMS) are:

- *No LCMSproposesa recommender system of contents for educational resources creation based on the learning domains, educational objectives, disciplinary competences, educational levels and learner dynamic model; they are limited to recommend existing resources to learners;*
- *Most of the existing ERS do not consider differences in learner model and its dynamic dimension;*
- *No LCMS applies a MLM method that takes into account the experience of teachers and also the variability of course contents.*

To overcome these limits, we propose learningand knowledge management systems (LKMS) that usesour proposal MLM-based educational recommender system (ERS), called Educational Knowledge Resources Assessment using Machine Learning & Networks (EKRAM). EKRAM analyses the contents based on machine learning models (MLMs) that explore educational and classification metadata of contents to assess them and identify the most relevant of them. Then, EKRAM organizes these most relevant contents to produce an educational resource for a specific usage, may enable a better learning digital process. More specifically, EKRAM allows to:

- *Harvest and aggregate educational contents and resources;*
- *Resolve multi-sources contents metadata mapping for a standard interoperable metadata model;*
- *Enrich harvested educational contents and resources;*
- *Identify and resolve broken links;*
- *Identify the most relevant resources for specific educational goal.*

EKRAM is based on our previous works: Semantic Metadata Enrichment Software Ecosystem (SMESE) [65-67], trusted smart harvesting [68, 69], classification metadata enrichment [70-74], identification of the most relevant papers (STELLAR) [75-77]. The remainder of the paper is organized as follows. Section 2 presents the related work. Section 3 describes the part 1 of MLM-based educational recommender system (ERS)and introduces its various algorithms while Section 4 presents the evaluation through a prototype and a number of simulations. Section 5 presents a summary and some suggestions for future work.

Related work: Our literature review will be focused on recommendation system in general and more specifically indigital educational resources. We will discuss about the use recommendation algorithms in digital education.

Recommendation Systems (RS): Recommender Systems (RSs) 12-24, 26-31, 32-37, 39] are used to help users find new items or services, such as movies, books, music, orcourses based on information about the user, or the recommended item. Today, the recommender systems have been using Machine Learning (ML) algorithms from the field of artificial intelligence.However, the ML field does not have a clear classification scheme for its algorithms, mainly because of the number of approaches and the variations proposed in the literature. M. Nilashi*et al.*[18] developed a new hybrid recommendation method based on Collaborative Filtering (CF) approaches to overcome the sparsity and scalability problems in CF algorithms accordingly to improve the performance of recommender systems using ontology and dimensionality reduction techniques. According to authors, using knowledge about items and users help to produce a recommendation based on knowledge and reasoning about which item meet the needs of users. Authors defined two main phases: (i) the recommendation models are constructed; in this phase several tasks are performed which are clustering the rating, dimensionality reduction using SVD and producing the similarities matrices of the items and users; they clustered the users' ratings on movies using Expectation Maximization (EM) algorithm; then for each cluster, they provided the semantic similarity calculation matrices from the movie ontology repository, and (ii) the prediction and accordingly recommendations tasks are performed for a given user, called target user; a ranked list of items is provided to be recommended by the recommender system to the target user; to do so, the target user is assigned to one of the clusters determined in the first phase; then SVD calculation is performed based on the past ratings to find the target user similarities to the other users (finding the neighbors of the target user); for item-based recommendation, they also performed same procedure for the items; finally, they combined user- and item-based predictions in a weighted approach. *Unfortunately, their approach is strongly related to a predefined ontology; they do not propose an evolutionary ontology based on machine learning.* As mentioned, this section presents an overview of RSs and focuses on the Chatbots in the context of Semantic Matching Systems (SMS).

Research in the area of Multi-Agent Robot Systems (MARS) [21, 40-52] has received wide attention among researchers in recent years; however, this research is more focused on the Human-Robot Interaction (HRI) to perforn some of human's physical tasks instead of Social Assistive Robotics (SAR)[45, 49, 51] such as Amazon's Alexa, Apple's Siri and Microsoft's Cortana. In both case, trust is critical to the success of multi-agent robot systems (MARS). According to[40-41, 44, 47], trust is a fundamental part of beneficial human interaction and it is natural to foresee that it will soon be important for HRI. S. Rossi*et al.*[45] shown by comparing Social Assistive Robotics (SAR) with Virtual Agents (VA) that are applications on mobile phones. Authors addressed the comparison between these latest two technologies in the context of movie recommendation, where the two considered interfaces are programmed to provide the same contents, but through different communication channels. According to authors, the main result arising from this study is that the SAR is preferred by users although, apparently, it does not change the acceptance rate of the proposed movies. *Unfortunately, use the SAR requires that users move to the cinema.* S. Herse *et al.*[49] conducted a vignette experiment to investigate the persuasiveness of a human, robot, and an information kiosk when offering consumer restaurant recommendation. They investigated the effect of robot persuasion on decision making when compared against the persuasiveness of non-social machines and humans. Authors found that embodiment type significantly affects the persuasiveness of the agent, but only when using a specific recommendation sentence. These preliminary results suggest that human-like features of an agent may serve to boost persuasion in recommendation systems. However, the extent of the effect is determined by the nature of the given recommendation. *As [45], the main drawback of Social Assistive Robotics (SAR) is the fact that it needs a physical presence.*

Knowledge Recommendation Systems (KRS): The rapid expansion of knowledge makes it increasingly difficult for users to obtain the precise necessary information even on an e-learning platform. Thus, knowledge recommendation [27, 38, 53-64] has become crucial to support learning. X. Yin*et al.*[53] proposed a knowledge recommendation approach that integrates the degree of correlation between knowledge and tasks, the feedback-based personal experience, the collective experience of designers, and the degree of demand for knowledge based on the forgetting curve. Specifically, authors presented a correlation-experience-demand (CED) integrated knowledge recommendation approach to solve the above four problems: "what to recommend", "when to recommend", "who to recommend" and "how to recommend". Their CED approach uses the workflow engine of the product data management (PDM) system to establish the relationship between the design process and tasks, which solves the "when to recommend" problem while The term frequency inverse document frequency algorithm (TF-IDF) and cosine similarity algorithm are adopted in each workflow node of the design process to compute the similarity between tasks and knowledge to find the knowledge that matches the task, which solves the "what to recommend" problem. Then, according to that individual's access to knowledge information, that individual's degree of demand model for knowledge is constructed based on the forgetting curve, which solves the "who to recommend" problem. Finally, the recommendation list is obtained by ranking the knowledge in assistance score descending order to build personalized and accurate knowledge recommendations, which solves the "how to recommend" problem. *The CED approach is more a correlation system between knowledge and tasks than a recommendation system; indeed, there is not learning process about the recommendation list. In addition, authors evaluated the user need of knowledge using his access to knowledge information based on the forgetting curve function; just the access to knowledge does not allow to know that the user has this knowledge.* L. Wen*et al.*[62] attempted to improve retrieval efficiency by proposing a digital literature resource organization model based on user cognition to improve both the content and presentation of retrieval systems. They focused on (1) resource organizations based on user cognition and (2) new formats on search results based on knowledge recommendations. They will purposefully employ data from users' own information and give knowledge back to users in accordance with the quote "of the people, for the people." Their core concepts and the relationships among the concepts are extracted through natural language processing. The relationships between concepts are either subordination and correlation. A triple consists of two core concepts and their relationship. *Authors just propose a contents classification system that derives a category tree from the contents. And then, recommend a content based on its categories. In addition, the recommendation does not take into account the user daily activities.*

Educational Recommendation Systems (ERS): S. Wan and Z. Niu. [2] proposed a hybrid filtering recommendation approach (SI – IFL) combining learner influence model (LIM) that is applied to acquire the interpersonal information by computing the influence of a learner exerts on others, self-organization based (SOB) recommendation strategy that is applied to recommend the optimal learner cliques for active learners by simulating the influence propagation among learners, and sequential pattern mining (SPM) that is applied to decide the final learning objects (LOs) and navigational paths based on the recommended learner cliques. LIM consists of learner similarity, knowledge credibility, and learner aggregation, meanwhile, LIM is independent of ratings. To optimize the LIM, authors proposed an intuitionistic fuzzy logic (IFL) to address the uncertainty and fuzzy natures of learners.

According to authors, their SOB recommendation approach achieves a stable structure based on distributed and bottom-up behaviors of individuals. *Unfortunately, authors approach is limited to recommend existing learning objects to student and ignored the creation of these learning objects according to the knowledge field.*J. K. Tarus*et al.* [3] proposed a hybrid knowledge-based recommender system based on ontology and sequential pattern mining (SPM) for recommendation of e-learning resources to learners. In their approach, authors used ontology to model and represent the domain knowledge about the learner and learning resources whereas SPM algorithm is used to discover the learners' sequential learning patterns. Mors specifically, their approach involved four steps: (1) creating ontology to represent knowledge about the learner and learning resources, (2) computing ratings similarity based on ontology domain knowledge and making predictions for the target learner, (3) generation of top N learning items by the collaborative filtering recommendation engine, and (4) application of SPM algorithm to the top N learning items to generate the final recommendations for the target learner.*As [2], their approach does not propose contents recommendation to create educational resources.*M. Maravanyika and N. Dlodlo [4] developed an adaptive recommender-systems-based framework for differentiated teaching and learning on eLearning platforms. Authors applied a Multi-Attribute Utility Theory (MUAT) to identify the 10 top attributes to go in as personalized learning framework components.

Based on the survey, the top ten (10) attributes were identified for inclusion in the personalised learning platforms: culture, emotional/mental state, socialisation, motivation, learning preferences, prior knowledge, educational background, learning/cognitive style, and navigation and learning goals.*This approach does not propose recommender system model; authors just propose a survey to identify top (10) attributes that impacts the recommender system.*M. Maravanyika*et al.* [5] proposed proposes a recommender-system-based adaptive e-learning framework for personalized teaching on e-learning platforms. According to authors, their framework would assist designers, teachers and learners to identify issues they need to consider in order to address challenges of poor engagement in online distance settings, arising from a "one-size-fits-all" approach that does not recognize the role of individual differences in teaching and learning. Authors also claimed that their framework may enable the identification of problems or obstacles that may be encountered when supporting learners in their quest to reduce frustration and boredom when using a Recommender-Based Pedagogical System (RBPS). In their proposed adaptive framework, we identified five dimensions, including real-time dynamic adaptation and context modelling in addition to the learner model, the domain model and the pedagogical strategy.*Unfortunately, authors do not take into account the dynamically adjusting the adaptation as learner variables.As [1 and [2], a contents recommendation model to create educational resources before recommend them to learners is not proposed.*Q. Hu et al. [6] proposed a multi-objective framework for learning peer recommendation based on dynamic interaction tripartite graph (DITG) and an attention-driven CNN (LPRACNN). Specifically, authors construct a DITG with manually assigned weights that reflect the complex relationships between learners and content from learning objective perspectives. Then, they devise two novel layers of a scaler layer and an attention-driven CNN to tune the initial weights of the DITG. The proposed attention-driven CNN is leveraged to tune the weights of interaction behaviours according to the features of the learning content. After obtaining different interaction intensities among learners, they optimize the proposed system in terms of diversity, novelty and interaction intensity. According to authors, their multi-objective function optimizes three conflicting metrics (interaction intensity, diversity and novelty) to achieve simultaneous multiple recommendations for a group of learners. *Unfortunately, their approach needs manual contribution; that is not scalable.*U. Deepthi *et al.* [7] proposed a course recommendation system designed to help the student to short-list the courses thatsuit the grades of the student. Their proposed course recommendation system gives some suggestion based on a set of rules. This set of rules is developed using the data of previous students who have successfully completed various courses. When a new student's data is given to the system, it searches for the previous students who have the data and also traces out the courses in which the previous students were successful. So, the attributes of the legacy data (data of previous students) and new data are matched thereby predicting the success of the student. The system provides a list of courses with better success probability that helps to reduce the confusion of the student as they get a better idea about the courses they have to focus on. *The authors' proposal is a good idea, unfortunately, the author do not take into account the experience of new teachers and also the variability of course contents.*As [7], L. Jinjiao*et al.*[8] proposeda course recommendation system. Specifically, authors proposed a sparse linear based technique for top-N course recommendation through both adding the expert knowledge and sparseness regularization in the computation. Their proposed method could extract the inner structure and information of the courses existed in the education management system from the student/course relationship by constraining the newly proposed regularization term optimized calculation.*As [7], authors do not take into account the experience of teachers and the variability of course contents.*G. Czibula*et al.* [9] proposed a new classification model, SPRAR for predicting the final result of a student at a certain academic discipline using relational association rules (RARs). Their classification model is a binary one (there are only two classes to predict: pass or fail), but according to authors, their proposed model can be extended for a multi-class classification problem (to predict the final grade of the student).*Unfortunately, authors do not propose solution to increase the student success rate.*In conclusion and according to the literature review:

- *Existing LCMS do not propose a recommender system of contents that will be used to provide new educational resources creation based on the learning domains, educational objectives, disciplinary competences, educational levels and learner dynamic model;*
- *Most of the existing ERS do not consider differences in learner model and its dynamic dimension;*
- *Existing LCMS do not apply a MLM method that takes into account the experience of teachers and also the variability of course contents.*

Educational Knowledge Resources Assessment using Machine Learning Ecosystem (EKRAM): In this section, we present the details of the proposed Functional Architecture. This figure represents the functions of the project EDUCATIO, the main function related to this article is Knowledge

Assessment Engine (KAE) and in theFig. 1 we describe conceptually the Educational Knowledge Resources Assessment including the KAE.

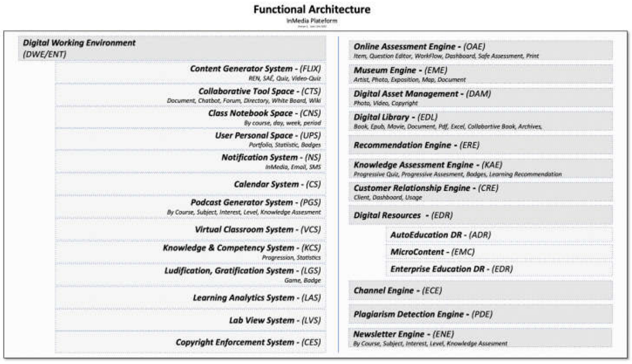

Fig. 1. Functional Architecture

Overview of EDUCATIOproject: In Fig. 2, we can see the major components of the project. On the left side 1) DIGITAL EDUCATIONAL RESOURCES (DER), 2) ASSESSMENT RESOURCES PROCESS, 3) ASSESSMENT LEVEL & LEARNING RECURSIVE PROCESS, 4) ASSESSMENT & CERTIFICATION PROCESS, and on the right side: 1) RESOURCES ENRICHMENT, 2) KAE LEVELS, 3) MLM RECOMMANDATION ENGINE, 4) KAE SURVEYS. All the process or component are involvedwith Knowledge Resources Assessment (KRA) and the Knowledge Assessment Engine (KAE).

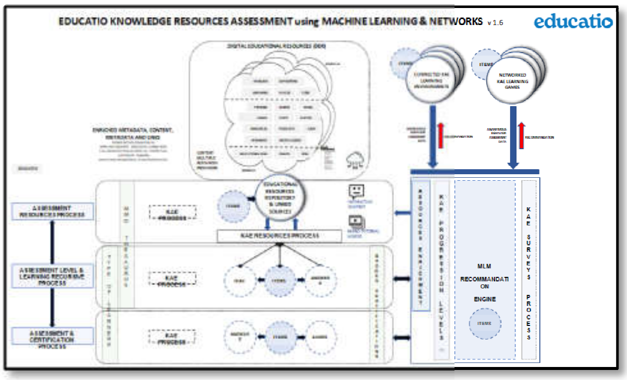

Fig. 2: EKRAM Overview Model

EKRAM Metadata Model

Educational knowledge resourcesassessment metadata model: Several rules have been proposed to cover the description and provision of access points for all educational resources. These rules are based on an individual framework for the description of these educational resources according to the learning goal and their semantic relationships. According to literature, the metadata play a key role in offering high quality services such as recommendation and search. Metadata can also be used for automatic educational resources quality control as, in the light of the continuously increasing number of educational resources, manual quality control is getting more and more difficult. In order to benefit effectively from metadata, they should be unified and standardized. Here, we proposed a unified and standard interoperable model, called educational knowledge resources assessment metadata model (EKRAM) whose objective is to match any known metadata model such as UNIMARC, MARC21, RDF/RDAand LOM to aEducatio Standard Model in order to be able to centralize educational resources into an unified repository.

EKRAM is applied at the first step of the Educatio knowledge resources conceptual process. For resources whose metadata does not follow any known model, Educatio Resource Preprocessor applies a machine learning model based on text mining and analysis algorithms that analyzes the metadata labels and their values in order to deduce which Educatio Standard Model metadata they correspond to; for example, if an educational resource is retrieved from a source that does not use a standardized metadata model and have a metadata with label "Category" and value "Mathematics", our algorithm will recognize, based on the resources already saved and validated that "Mathematics" is rather a metadata of the label "Discipline" than "subject".

EKRAM Algorithms: In this section, we describe the different algorithms of the proposed model Educational Knowledge Resources Assessment using Machine Learning & Networks (EKRAM). EKRAM applies several algorithms to perform features such as:

- *Multi-source harvesting auto-adaptive algorithm;*
- *Educational resources auto-classification algorithm;*
- *Educational resource discovery and recommendation algorithm.*

Multi-source harvesting auto-adaptive algorithm

For the *Auto-adaptive multi-source harvesting algorithm*, we adapted our previous algorithms, trusted smart harvesting [68, 69], in order to take into accounting the digital educational resources.The metadata are specifics and adjustedfor our Educatio Knowledge Resources Metadata Model.

Educational resources auto-classification algorithm: In addition, EKRAM use our previous works for *educational resources auto-classification* [70-74]. We modified and improved the books topics, emotions and sentiments extraction algorithms in order to detect the educational classification metadata.

Educational Resource Discovery & Recommendation algorithm: EKRAM proposes an algorithm that aims is to discover and recommend relevant resources according to the specific educational goal, called Educational Resource Discovery and Recommendation algorithm (ERDR).In contrast to existing educational recommender system, ERDR organizes in specific using order the recommended educational items or resources to propose step-by-step learning adapted to each learner. Based on the discovery resources into our Educational Resources Repository & Linked Sources (see in the previous page, Fig. 2) andpublicly available external resources repository such as Wikipedia (www.wikipedia.org), YouTube (www.youtube.com), Google museum (artsandculture.google.com) and Open Educational Resources (www.oercommons.org), ERDR automatically and collaboratively builds educational resources based on educational items; an educational item denotes an elementary object that may be obtained in a resource: a chapter, a paragraph, a game, an image, a video, an audio, a section, a quiz, a link, etc. For example, to assist a teacher to create a new educational resource, ERDR may recommend the chapter 3 of resource A, the last paragraph of resource B, the game included in the resource C, the image of the resource D, the introductive video of the resource E and the quiz of the resource F. ERDR is a knowledge-oriented resources generator; in order world, ERDR goal is to assist resources editors or teachers to create resources not for learning, but to allow the acquisition of a very specific knowledge.With an interactive user interface, EKRAM supports collaborative real-time resources creation whereby an activity book is generated from user resources and queries. An explicit relevance feedback mechanism allows user feedback to reformulate the query for additional searches. To perform it, ERDR of EKRAM must perform two main tasks: (1) identify the educational items and (2) recommend the items according to the editor's or teacher's criteria; in the following paragraphs, we present these two processes.

Educational items identification process:

Fig. 3 illustrates the ERDR process to identify the educational items. Notice that this process is applied to each new resource into Educational Resources Repository & Linked Sources or as soon as a resource is modified; the output of the educational item identification process is an Educational Items Repository.

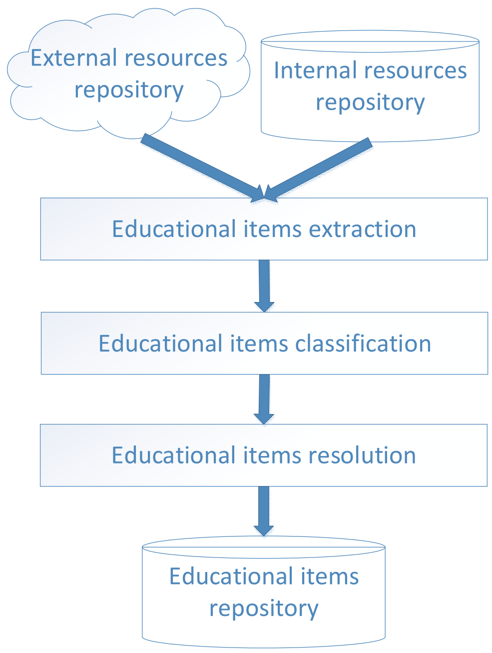

Fig. 3. ERER educational items identification process

From the external and internal resources, we first extract the items of the given educational resources.For external resources repository, we used our harvester model proposed in [68, 69]. In these proposals, we present a system which utilizes information retrieval techniques to intelligently harvest online resources. As mentioned above, educational item is an elementary object that may be identify in a given resource. After the extraction, we perform each item classification metadata semantic cataloguing. Indeed, each extracted educational item is catalogued as a new bibliographic record in the educational item repository. For the classification metadata of educational item, the value of each of them is not a constant value, but a vector of constant value with coefficient. Let L_e^m denotes the list of explicit value of the classification metadata *m*; L_e^m is the same list of value of the classification metadata of the original resource. L_d^m denotes the list of detected value of the classification metadata *m*; L_d^m is obtained based on our MLM-based topic detection proposed in [70-74]. These algorithms combine the machine learning model such as natural language processing (NLP), text and data mining (TDM), semantic information retrieval (SIR), and semantic topic detection (STD). We improved our previousmodels[70-74] to take into our model: the video, image and audio. Notice that our previous models used a text as input and topic, emotion and sentiment as output. In other words, we used machine learning approaches to detect topics, emotions and sentiments in a given text; so, a *text-based tags detection model*.

To take into account the image, we proposed an *image-based tags detection model* that is content-based image retrieval (CBIR) which uses our image-tagging ontology and Educatio images repository to detect hidden tags into a given image. To take into account the audio, we apply a Speech-To-Text algorithm to extract the text to the audio; then, we apply our *text-based tags detection model* to detect hidden tags into this extracted text. To take into account the video, we separate the audio and the set of images. For the audio, after applying the Speech-To-Text process, we used our *text-based tags detection model* to detect hidden tags into this extracted text. For the set of images, we apply our *image-based tags detection model* to detect hidden tags into the images. So, any type of educational item may be process to detect hidden tags; hidden tags that will be used to find classification metadata value of educational items; for a classification metadata *m*, we define the list of detected value L_d^m. As mentioned above, each classification metadata of an educational item is a vector of a constant value with coefficient; let $\langle (d_1,\omega(d_1,m)),(d_2,\omega(d_2,m)),...,(d_i,\omega(d_i,m)),...,(d_n,\omega(d_n,m)) \rangle$ be thevector of classification metadata*m* where $\omega(d_i,m)$ denotes the coefficient of classification metadata value d_i; for example, for the classification metadata *[educational discipline]*, we may have the vector $\langle (\text{Mathematical},1),(\text{French},3),(\text{Science},1),(\text{Geography},2),(\text{History},2) \rangle$. To determine the vector, we compute the coefficient of the value d_i for classification metadata *m*as follows equation:

$$\omega(d_i,m) = 1 + P(d_i,L_e^m) + P(d_i,L_d^m) \quad (6)$$

where $P(d_i, L_x^m)$ is defined as follows:

$$P(d_i,L_x^m) = \begin{cases} 1 & if \ d_i \in L_x^m \\ 0 & if \ d_i \notin L_x^m \end{cases} \quad (7)$$

To avoid the bibliographic record of educational item duplication, we apply our previous entity resolution approaches proposed in [68, 69].

Educational items recommendation process: To find relevant items, the recommendation process is primarily based on the educational resource profile and user precision. As shown in Fig. 4, using educational profile parameters (resource profile to be generated) and educational item ontology, we normalize the information given by the user as educational resource profile; this task is illustrated by ***"Concept normalization"***. Notice that the educational item ontology is build based on the expert user annotations; educational item ontology helps to build educational domain model that contains all the knowledge for a particular discipline.

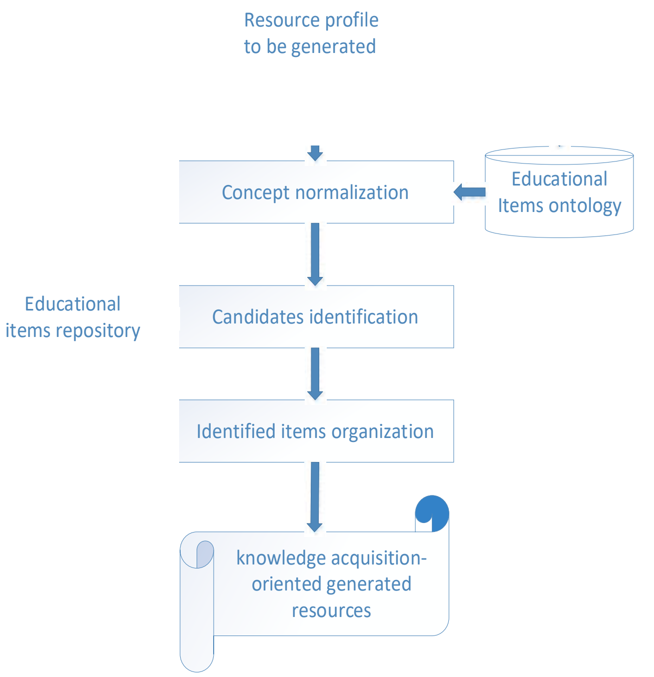

Fig. 4. ERER Educational items recommendation process

First, we split the domain in four layers the first represents the category of courses and each category is divided on several courses, and each course is presented by a set of concepts. Second, we match concepts from the educational item ontology in the classification metadata and calculate the importance score for each concept using term frequency-inverse document frequency (tf-idf). Before the matching, user request data preparation is an important issue for all methods used in data mining, as real-world data tends to be missing (lacking attribute values or certain attributes of interest), noisy (containing errors, or outlier values which deviate from the expected data); this action allows to obtain the resource profile to be generated (see Fig. 4).

After *"Concept normalization*" that transformed or consolidated user request data into forms appropriate for mining, we perform *"Candidate identification"*. Candidate identification aims is to identify the candidate educational items related to the concepts in the user request data. The similarity between the content/description of educational item and that of the description in the personal parameter of user when each content of educational item and description in the personal parameter of user is represented as a tf-idf vector using all vector space concepts in the educational item ontology.

The content similarity is calculated by the cosine similarity between tf-idf vectors and top Z educational items with high similarity are included in the candidate set. In order to organize identified educational items at the previous step in a format of a personalized learning resource similar to activity book, we perform an *"Identified items organization"* step.This step tries to answer the following question: What is the best item before and after a given item?Let $S = \{I_1, I_2, ..., I_i, ..., I_z\}$ be the set of identified educational items obtained after the *"Candidate identification"* step;
Fig. 5 illustrates the organizational issue.

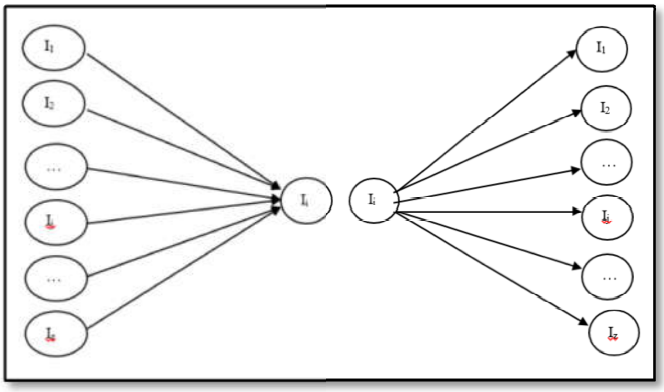

Fig. 5. Illustration of items organization issue

Let BI_i be the set of items before I_i in the original risource of I_i and AI_i be the set of items after I_i in the original risource of I_i. We evaluate the weight of I_j to be before I_i into the new resource as follows:

$$B(I_j, I_i) = \frac{Sim(I_j, BI_i)}{\sum_{k=1}^{z} Sim(I_k, I_i)} \tag{8}$$

where $Sim(I_j, BI_i)$ computes the sum of cosine similarity between I_j and each item of BI_i. We evaluate the weight of I_j to be after I_i into the new resource as follows:

$$A(I_j, I_i) = \frac{Sim(AI_i, I_j)}{\sum_{k=1}^{z} Sim(AI_i, I_k)} \tag{9}$$

where $Sim(AI_i, I_j)$ computes the sum of cosine similarity between I_j and each item of AI_i.Finally, we define an algorithm that aims is to transform our items set $S = \{I_1, I_2, ..., I_i, ..., I_z\}$ into anoriented graph with weighted edge G. The algorithm is defined as follows:

Fig. 6 illustrates the graph G for $|S| = 10$.To organize the items, we need to find the ***Hamiltonian path*** with the greatest sum of the weights of the edges. A Hamiltonian path is a path in the graph that passes through all the nodes once and only once.In our case, we adapted the existing algorithm to find the Hamiltonian path due to the fact that : (1) we identify the source node (first item of the generated and organized educational resource) and end node (last item of the generated and organized educational resource) and (2) we compute the longer paths because the greater the weight of a edges, the stronger the order relation.

The source node is defined as the node with the smallest number of outgoing edges while the end node is defined as the node with the highest number of incoming edges. For example, in the

Fig. 6, I_2 is the first item and I_8 the last item. Let G=(V,A) be the oriented graph with weighted edge and Φ be the Hamiltonian path of G to find.

Table 1. Pseudo code to transform set S into Graph G

1.If $\left(B(I_i,I_j) > B(I_j,I_i)\right) and \left(A(I_j,I_i) > A(I_i,I_j)\right)$ then

a.item I_i must be before I_j

b.oriented edge value $\Omega(I_i,I_j) = 2$

2.If $\left(B(I_j,I_i) > B(I_i,I_j)\right) and \left(A(I_i,I_j) > A(I_j,I_i)\right)$ then

a.item I_j must be before I_i

b.oriented edge value $\Omega(I_j,I_i) = 2$

3.If $\left(B(I_i,I_j) > B(I_j,I_i)\right) and \left(A(I_i,I_j) > A(I_j,I_i)\right)$ //there is a confusion

a.If $\left|B(I_i,I_j) - B(I_j,I_i)\right| > \left|A(I_i,I_j) - A(I_j,I_i)\right|$, then

i. I_i must be before I_j

i.oriented edge value $\Omega(I_i,I_j) = 1$

b.Else, then I_j must be before I_i

i. I_j must be before I_i

i.oriented edge value $\Omega(I_j,I_i) = 1$

Table 2. Pseudo code to find best Hamiltonian path of G from *I_i to I_j*

1.Find all the Hamiltonian path of graph G from I_i *to* I_j

2. $w(\Phi) = 0$

3.For each Hamiltonian path *P* of graph G from I_i *to* I_j

i.Compute the weight of *P using equation*

ii.If $w(\Phi) < w(P)$, $\Phi = P$

Table 3. Description of dataset

Number of users	Number of disciplinary competences	Number learning items per disciplinary competences
50	70	1000

Let I_i be the source node and I_j be the end node. The algorithm to find Φ is defined as follows:

Prototype Applications and Performance Evaluation: In this section, we present the experimental evaluation of our proposed architecture. The objective of our experimental evaluation is to compare, according to the literature, more recent and performing algorithms on various types of entities.

Prototype applications: Our proposed model led to the conceptualization and prototyping of EDUCATIO (https://proto.educatio.ai/), a Learning Management System (LCMS) mainly designed (1) to assist teachers to createeducationalresources for specific educational profile (educational goal, educational level, educational domains, educational discipline, disciplinary competences) by recommending relevant contents, relevant chapter, relevant resource sections and (2) to recommend relevant educational resources to learners for specific goal or the progressive acquisition of specific knowledge.

Experimental setup: We have conducted a set of experiments to set parameters and examine the effectiveness of our proposed recommender system in terms of user's satisfaction according to the feedback iterations number. The experiment was carried out in the InMedia technologies research Lab where e-learning is used to support teaching and learning.

A group of 50 users participated in the experiment. The teachers created multiple learning items than may be combined to obtain learning materials for courses in the context of e-learning portal accessible by the students for their learning. The prototype allows the users to access the learning items and materials, and courses as well as rate them on a scale of 1 – 5 (1 – very irrelevant, 2 – fairly irrelevant, 3 – irrelevant, 4 – relevant, 5 – very relevant). Our recommender system (EKRAM) may then recommended ordered list of educational items for step-by-step learning. As comparison terms, we use the approach BBookX described in [78].

Datasets and measurement criteria: Our dataset is a dataset obtained from 50 users using the learning management systems (LCMS), in undergraduate schools. The dataset was collected within a period of 6 months. The Table 3 illustrates the detailed description of the dataset and learning materials. For the purpose of evaluating EKRAM model, we split the dataset into training set (75%) and test set (25%) randomly. In this experiment, the performance measurement criteria are (1) the rate (satisfaction level) of teachers according to the number of their feedback iteration and (2) the number of their feedback iteration according to the number of chapters.

Experimental Results: In Fig. **8**, we evaluate the average number of the feedback iteration when varying the number of chapters while in Fig. **9** shows the average rate of teachers varying with the number of chapters. For the experiment in Fig. **8**, the rate is fixed to 5, while in Fig. **9**, the number of chapters is fixed to 10. In Fig. **8**, we observe that for EKRAM and BBookX,the average number of the feedback iteration increases with the number of chapters; the teacher's rate is fixed to 5.

Fig. **8** also shows that EKRAM outperforms BBookX.For example, the gap of the average number of the feedback iteration between EKRAM and BBookX is, for 1 chapter (resp. 5 and 10), is 1.25 (resp. 4.15 and 4.04); that means that, the gap increases with the number of chapters.

Overall, the average relative improvement of EKRAM compared with BBookX is about 4 feedback iteration; that means that EKRAM is more performing in the context of more chapters.

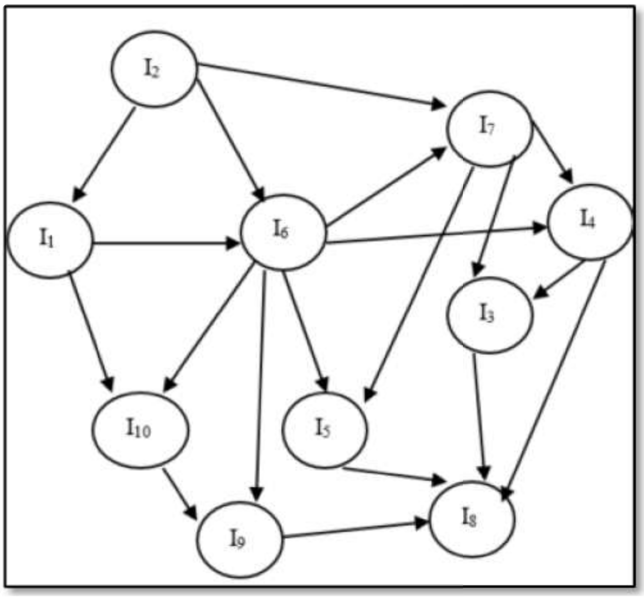

Fig. 6. Illustration of graph G for z=10

Fig. 7. Prototype applications

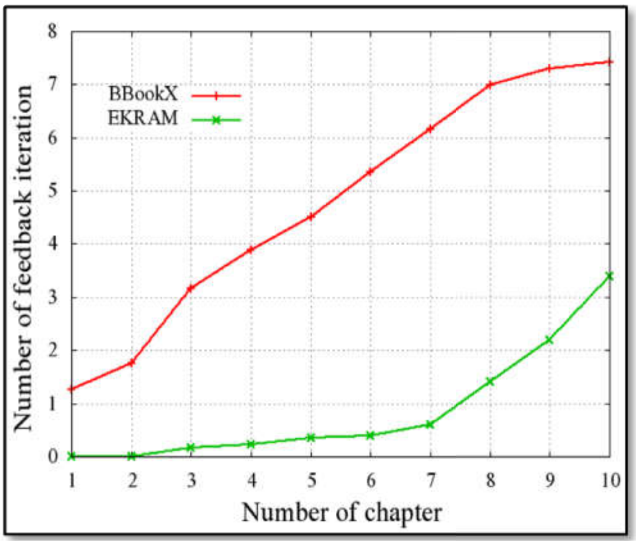

Fig. 8. Number of chapter Vs Number of feedback iteration

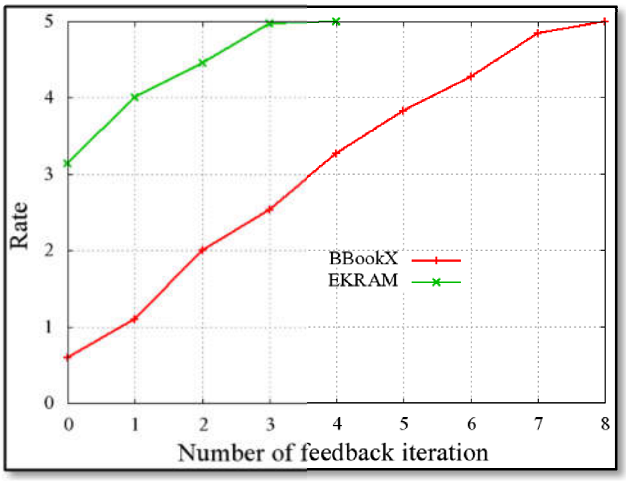

Fig. 9. Number of feedback iteration Vs Rate

Fig. 9 presents the average rate (users' satisfaction level) with varying the number of the number of the feedback iteration; the number of chapters of proposed learning materials is fixed to 10.We observe for the both approaches that average rate increases with the number of the feedback iteration.

Fig. 9 shows that EKRAM outperforms BBookX; the gap of the average rate between EKRAM and BBookX is, for 0 feedback (resp. 2 and 4), is 2.54 (resp. 2.46 and 1.18); that means that, the gap decreases with the number of feedbacks.
Fig. 9 also shows that, after 3 feedbacks, the teachers who used EKRAM found that the proposed learning materials is very relevant while those who used BBookX found that the proposed learning materials is very relevant after about 8 feedback iteration. This can be explained by the fact that EKRAM combines learner educational profile and learning style; in additional, EKRAM uses dynamics and adaptive learning scenarios, and adaptive learning object Media (text, audio, video, image, quiz, graphic, forum, wiki, etc.).

Future work: Our future work will focus mainly on the part two of the same subject: Educational Knowledge Resources Assessment using Machine Learning & Networks. This part II will make emphasis on: 1) The recommendation of items as recommended items for a specific exam of a specific level of KAE (Knowledge Assessment Engine). This recommendation uses the items MLM and a collaborative bank of items; 2) The auto-cataloguing of items in their creation and the recommendation of an item into an exam for the 7 levels of KAE.

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