Adaptive Support for Student Learning in an e-Portfolio Platform by Knowledge Discovery and Case-based Reasoning

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***Abstract*—Constructing an e-portfolio platform for students is a modern educational trend. However, a student's learning context is not analyzed in the current e-portfolio platform. In this research a model was designed for identifying the specific learning context and providing the corresponding knowledge support. A system framework which uses advanced information techniques is proposed. *Information Retrieval* (*IR*) technique extracts and analyzes key concepts from the student's previous e-portfolio records. The data mining technique discovers hidden knowledge rules from key concepts. Various context-knowledge views were constructed based on discovered knowledge rules. Besides, *Case-Based Reasoning* (*CBR*) and profiling techniques were used to identify learning context and design adaptive knowledge recommendation mechanisms. Therefore, after identifying current learning contexts, the system would recommend previously documented knowledge to assist the student. A prototype system was developed to demonstrate the effectiveness of providing knowledge to help students solve learning problem(s).**

***Index Terms*—e-portfolio, learning context, data mining, adaptive knowledge support**

I. INTRODUCTION

Constructing an e-portfolio platform for students is a modern educational trend [6][14][15]. Various e-portfolio platforms have been built by schools [41][42]. Students record relevant information of learning activities, such as credits, scores, and reports, in an e-portfolio platform. Therefore, an authorized user can access and review the student's e-portfolio records, e.g., a corporation manager can check up on the staff's development. Besides, workers can outline evidence from e-portfolio records to show specific career-ability.

Effective learning is always key in compulsory education. In the past, the evaluation of effective learning was only based on some final results from formal learning activities. However, in the current diversified educational environment, results of official learning activities do not seem to be enough in determining effective learning. Schools unofficially evaluate activities with a macro-view (e.g. career training, license testing, and science games) in the learning context. If learning is not effective, the school needs to use knowledge gathered from relevant information and previous cases to clarify the causes of a student's learning problem(s). Then the school provides support to help the student solve his or her learning problem(s). *Case-Based Reasoning* (*CBR*) techniques have been widely used to help workers solve problems [8][19][24][27][30][40]. Conventional *CBR* approaches focus on identifying similar problems without exploring the relevant context of a problem. Thus, identifying similar cases through *CBR* is not sufficient to solve learning problems. A knowledge support framework is essential so that students have information necessary to take appropriate action to solve learning problem(s).

In this work, a knowledge support system for effective learning is proposed. Besides adopting *CBR* to identify similar cases, text mining techniques were used to compensate for the shortcomings of *CBR*. For specific learning activity, its features, context information and relevant information (documents) accessed by students are recorded in the e-portfolio records. Historical codified knowledge (textual documents) can provide valuable knowledge for solving the current learning problem.

In the proposed system data mining methods were used to discover learning activity context rules from the e-portfolio records. Learning activity context rules identify frequent associations between learning activity features and relevant context characteristics. The system then used learning activity context rules to discover more learning activity features to assist *CBR* in learning activity identification. For example, the learning activity feature collected by e-portfolio platform was "*Study Project*". The learning activity context rule indicated that the learning activity feature "*WebService.WSDL*" was frequently associated with the learning activity feature "*Programming.ObjectOrientedConcepts*" and the context of "*Network_Management.SOAP*". The discovered learning activity feature provided *CBR* with more clues for learning activity identification.

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Moreover, the proposed system employed *Information Retrieval* (*IR*) techniques to extract the key concepts of relevant information necessary to handle a specific learning activity. The extracted key concepts formed a learning activity profile that modeled the information needs of students for handling learning activities in certain context. The system then used the learning activity profile to gather existing and new relevant knowledge documents for specific learning activity according to the context information.

The remainder of this paper is organized as follows: Section II reviews related works on knowledge management and knowledge discovery. Section III introduces the proposed framework for knowledge support in a learning context. Section IV describes the discovery of knowledge. The knowledge support is discussed in Section V. The prototype system is demonstrated in Section VI. Finally, in Section VII, conclusions are presented.

II. Related WorkS

The related literature covers knowledge management, e-portfolio, context, case-based reasoning, information retrieval, and data mining techniques.

A. Knowledge management and knowledge retrieval

Artificial Intelligence (*AI*) techniques have advanced knowledge management, including knowledge acquisition, knowledge repositories, knowledge discovery, and knowledge distribution [26]. Knowledge acquisition captures tacit and explicit knowledge from domain experts [23][24], while knowledge repositories formalize the outcomes of knowledge acquisition and integrate knowledge in distributed corporate environments [18]. Taxonomy and mapping mechanisms are used to represent relevant knowledge and construct a framework for building a knowledge repository [7]. Knowledge discovery and mining approaches explore relationships and trends in the knowledge repositories to create new knowledge [33]. In addition, heuristic mechanisms, such as proactive knowledge delivery and context-aware knowledge retrieval, are used to enhance knowledge distribution [1].

A repository of structured, explicit knowledge, especially in document form, is a codified strategy for managing knowledge [11][17]. However, with the growing amount of information in organization memories, *Knowledge Management Systems* (*KMS*) face the challenge of helping users find pertinent information. Accordingly, knowledge retrieval is considered a core component in accessing information in knowledge repositories [16][25]. Translating users' information needs into queries is not easy. Most systems use *Information Retrieval* (*IR*) techniques to access organizational codified knowledge. The use of *Information Filtering* (*IF*) with a profiling method to model users' information needs is an effective approach that proactively delivers relevant information to users. The technique has been widely used in the areas of *Information Retrieval* and *Recommender Systems* [21][29][31]. The profiling approach has also in some cases been adopted by *KMS*' to enhance knowledge retrieval [1][2][12], whereby information is delivered to task-based business environments to support proactive delivery of task-relevant knowledge [1][16][28].

B. E-portfolio and context

Originally, the *Portfolio* presented the best works of literature and art as evidences for a job, show and personal achievements. Until 1980, it was used in the education domain and transformed into digital format as *e-portfolio* by Information Technology, e.g., voice, image, text, and multimedia; not be restricted by computer media type.

According to the definitions [37], context is the location of the user, the identities of people and objects that are near the user, and the status of the devices the user interact with. Context-aware is user adapted to the software execution environment involved with relevant context changing. Context is defined [13] as any information that characterizes the situation of an entity, where the entity can be a user, place, service, service relevant objects, etc. The context is categorized into location, identity, activity, and time types. A context-aware system uses context to provide relevant information and/or services to the user, where relevancy depends on the user's task [9]. The "environment" is used to replace "activity" in the context categorization [34]. These context types are used to characterize the situation of a particular entity. By these types of context information, they can provide the information of who, what, when, and where of a particular entity.

A student constructs a personal e-portfolio to review his or her self-learning process. E-portfolio also assists the teacher to provide a modified teaching model for the student to facilitate effective learning. According to learning context, constructing an e-portfolio platform and providing adaptive knowledge support for students based on their learning profile is a modern educational trend [15][22].

C. Case-based reasoning

Various approaches integrating *AI* techniques have been proposed for problem solving [8][19][24][27][30][40]. *Case-Based Reasoning* (*CBR*), which has been widely used to help workers solve problems, is the process of solving a given problem based on the knowledge gained from previous solutions to similar problems. Most *CBR* systems include the following steps: case representation and storage, precedent matching and retrieval, adaptation of the retrieved solution, validation of the solution, and case-base updating to include the information gained from solving the new problem. The *CBR* approach was used to implement a self-improvement helpdesk service system [8], and a *CBR*-based decision support system was developed for problem-solving in a complex production process [30]. More recently, B. S. Yang, T. Han, and Y. S. Kim [40] proposed integrating the *CBR* approach with ART-Kohonen neural networks (ART-KNN) to enhance fault diagnosis in electric motors. Moreover, RBCShell was

introduced as a tool for constructing knowledge-based systems with *CBR* [19], whereby previously solved problems are stored in the case memory facilitate problem-solving in new cases.

D. Information retrieval in a vector space model

The key contents of a codified knowledge item (document) can be represented as a term vector (i.e., a feature vector of weighted terms) in *n*-dimensional space, using a term weighting approach that considers the term frequency, inverse document frequency, and normalization factors [35]. The term transformation steps, including case folding, stemming, and stop word removal, are performed during text pre-processing [32][36][39]. Then, term weighting is applied to extract the most discriminating terms [5]. Let d be a codified knowledge item (document), and let $\vec{d} = <w(k_1, d), w(k_2, d), \ldots, w(k_n, d)>$ be the term vector of d, where $w(k_i, d)$ is the weight of a term k_i that occurs in d. Note that the weight of a term represents its degree of importance in representing the document (codified knowledge). The well-known *tf-idf* approach, which is often used for *term (keyword) weighting* [32], assumes that terms with higher frequency in a document and lower frequency in other documents are better discriminators for representing the document. Let the term frequency $tf(k_i, d)$ be the occurrence frequency of term k_i in d, and let the document frequency $df(k_i)$ represent the number of documents that contain k_i. The importance of k_i is proportional to the term frequency and inversely proportional to the document frequency, which is expressed as (1):

$$w(k_i, d) = \frac{1}{\sqrt{\sum_i \left(tf(k_i, d) \times \log(N/df(k_i) + 1)\right)^2}} tf(k_i, d) \times (\log \frac{N}{df(k_i)} + 1) \quad (1)$$

where N is the total number of documents. Note that the denominator on the right-hand side of the equation is a normalization factor that normalizes the weight of a term.

Similarity measure: The cosine formula is widely used to measure the degree of similarity between two items, x and y, by computing the cosine of the angle between their corresponding term vectors $\vec{x}$ and $\vec{y}$, which is given by (2). The degree of similarity is higher if the cosine similarity is close to 1.0.

$$sim(x, y) = \text{cosine}(\vec{x}, \vec{y}) = \frac{\vec{x} \bullet \vec{y}}{|\vec{x}||\vec{y}|} \quad (2)$$

E. Data mining

Data mining, which has become an increasingly important research area, involves several tasks, including association rule mining, sequential pattern mining, clustering, classification, and prediction [10][20]. Association rule mining and sequential pattern mining were used to extract knowledge patterns from previous problem-solving instances.

Association rules mining. Association rule mining tries to find an association between two sets of products in a transaction database. R. Agrawal, T. Imielinski, and A. N. Swami [4] formalized the problem of finding association rules as follows. Let I be a set of product items and D a set of transactions, each of which includes a set of products that are purchased together. An association rule is an implication of the form $X \Rightarrow Y$, where $X \subset I, Y \subset I$, and $X \cap Y = \Phi$. X is the antecedent (body) and Y is the consequent (head) of the rule. Two measures, support and confidence, are used to indicate the quality of an association rule. The support of a rule is the percentage of transactions that contain both X and Y, whereas the confidence is the fraction of transactions containing X that also contain Y.

Sequential pattern mining. The input data is a set of sequences, called data-sequences. A data-sequence is a list of transactions, each of which is a set of literals, called items. Typically, a transaction-time is associated with each transaction. A sequential pattern also consists of a list of sets of items. Sequential pattern mining finds all sequential patterns from a time-based transaction database [3].

The support of an association rule or sequential pattern indicates how frequently the rule applies to the data. A high level of support corresponds to a strong correlation between the product items. The *Apriori* algorithm [4] is typically used to find association rules by discovering frequent item-sets (sets of items). An item-set is considered to be frequent if its support exceeds a user-specified minimum support. Association rules or sequential patterns that meet a user-specified minimum confidence can be generated from the frequent item-sets.

III. System Framework of Adaptive Knowledge Support for Effective Learning

In this section, the proposed system framework description includes the concepts learning activity and learning context, knowledge requirements for evaluating learning status, and the proposed knowledge support framework. The system environment is a school's e-portfolio platform. The feature items in e-portfolio records were explored and information techniques were used to analyze and discover hidden knowledge rules. The discovered knowledge rules and student profiles were used to design context-knowledge views [38] and an adaptive recommendation mechanism. The proposed system recommended reasonable knowledge documents based on a student's learning context.

A. Learnin g Activity and Learning Context

A *learning activity* is what a student does in terms of learning in a specific domain for a period of time. For example, a specific course in a school promotes the learning of a skill(s) as a learning activity. The *learning context* is composed of a series of learning activities. This may involve several semesters and academic years. Because of the diversification of modern education, the student's learning context may not only include official activities (e.g., courses) but also comprehensive activities. A school can arrange for students to have practical training, license testing, and science research activities, etc. A student can join a society or team according to his interest. Besides, students can also be involved in

overseas study. These different learning activities enrich a student's learning context.

B. Knowledge Requirements for Evaluating Learning Status

Some difficulties may be encountered which can influence learning. A school would try to provide timely support. A student's *learning status* indicates whether his or her learning is effective or not. The school would construct an evaluation mechanism to monitor the student's learning status. In the modern diversified educational environment, evaluation based on a few results of some learning activities is not enough, so the school would refer to information relevant to the learning context to determine learning status. Therefore, to assist effective learning, not only association knowledge in a single learning activity is required, but also sequential knowledge across different learning activities in the learning context. Besides, knowledge needs to be profiled regarding student information requirements in a learning context.

C. Knowledge Support Framework for Learning Context

The proposed knowledge support framework for a learning context is shown in Figure 1. The system framework comprises the learning context, learning activity context rule discovery, learning activity profile discovery, and knowledge recommendation modules.

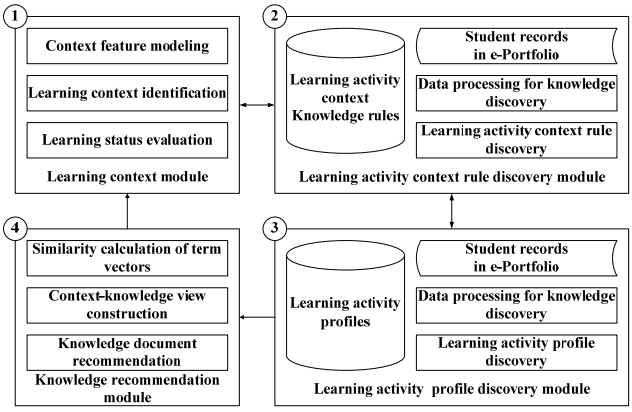

Figure 1. Knowledge support framework for learning context

1) Learning context module

This module gathered run-time information of a student's learning activities, such as learning features and context information. *CBR* used the collected learning features to retrieve and infer similar learning context cases. According to the identified learning context and context-knowledge view based on the knowledge recommendation module, the system evaluated the student's learning status and recommended relevant knowledge documents. The specific learning context, including learning activities and corresponding knowledge documents, was recorded in the records of the e-portfolio.

2) Learning activity context rule discovery module

This module describes the learning activity, the learning activity features and the relevant context information from the learning context module. The framework used association rule mining to discover the association between features and relevant context characteristics in a learning activity. Sequential pattern mining discovered the association across-learning activities. The discovered context knowledge rules were used to construct various context-knowledge views for a specific learning context.

3) Learning activity profile discovery module

For this module the records were searched to discover learning activity profiles. For a specific learning activity in a certain context, the relevant information (documents) accessed by the student was recorded in the e-portfolio record. The previously codified knowledge (textual documents) can also provide valuable knowledge for making the learning activity more effective. *Information Retrieval* (*IR*) techniques were used to extract the key terms from relevant documents of a specific learning activity for a certain context. The extracted key terms were used to construct the learning activity profile, which was then used to model the information needs of the student in a certain context.

4) Knowledge recommendation module

For this module the relevant documents were recommended for a learning activity as knowledge support. As noted previously, the learning activity profiles were used to gather existing and new relevant knowledge documents of a specific learning activity for a certain context. The documents relevant to a learning activity helped determine the clues for effective learning. The relevant documents provided practical knowledge support to help effective student learning.

IV. SYSTEM MECHANISM FOR ADAPTIVE KNOWLEDGE SUPPORT

In this section the procedures for discovering knowledge from e-portfolio records are described. To illustrate the proposed approach, the records of an e-portfolio platform which included the background and professional domains of a teacher, the working procedures for a learning activity, student score, creative student work, official games, society involvement, license and practical training information, etc. were used. Before being recorded in the e-portfolio platform, these data had already been digitalized and normalized. That facilitated the processing of the student's learning activity features and attributes. Besides, the system also extracted the student's learning status regarding the specific context.

Each learning activity was characterized by terms, features, and attributes. For example, the syllabus of an official course included outline description, concept introduction of each chapter, test, and homework features, etc. Besides, the teacher, department, time, and classroom information also formed the attribute set. These context features and attributes were recorded in the e-portfolio platform. It also retained the student's learning results. So the system could easily access characterized a specific learning activity. The learning context was composed of an activity or a series of activities. The composed information was stored in an e-portfolio platform. When the current context information of a student's learning activities was collected, CBR used it to infer the most

likely learning context determining the current learning context.

Extraction of identifying term vectors. In a specific learning activity, a student may have various information requirements. For example, when a *Computer Science* (*CS*) student studies a programming course, he may access object-oriented concepts and Java language specifications for homework or a test. Besides, relevant documents also help him to identify the concepts clearly, such as inheritance or encapsulation of object-oriented concepts. Based on the student's information requirements and relevant context information for a specific learning activity, the system uses terms weighting and retrieves the key terms from the course descriptions, features, attribute sets, and accessed documents for a learning activity to form a specific profile for it. These key terms form the terms vector and the profile for a specific learning activity. Let T_j be the set of identifying terms extracted from the outline description of a learning activity case C_j. An identifying term vector $\vec{C}_j$ is created to represent C_j. The weight of a term t_i in $\vec{C}_j$ is defined by (3).

$$w(t_i, C_j) = \begin{cases} 1 & if\ t_i \in T_j \\ 0 & otherwise \end{cases} \tag{3}$$

Equation (4) defines the similarity value $sim^T(C_k, C_j)$ of two learning activity cases C_k and C_j based on their concept introductions. The similarity value is derived by computing the cosine value of the identifying term vectors of C_k and C_j.

$$sim^T(C_k, C_j) = \text{cosine}(\vec{C}_k, \vec{C}_j) = \frac{\vec{C}_k \bullet \vec{C}_j}{|\vec{C}_k||\vec{C}_j|} \tag{4}$$

Similarity value by attribute. An attribute value may be nominal, binary, or numeric. For numeric attributes, a data discretization process is conducted to transform their values into value ranges or user-defined concept terms (such as low, middle or high). Equation (5) defines the similarity value $sim^A(C_k\ (attrb_x), C_j\ (attrb_x))$ of two cases C_k and C_j, derived according to their values of attribute x; value(C_k ($attrb_x$)) denotes the transformed value of attribute x of C_k , which is calculated by the discretization process.

$$sim^A(C_k(attrb_x), C_j(attrb_x)) = \begin{cases} 1 & \text{if value}(C_k(attrb_x)) \text{ equals value}(C_j(attrb_x)) \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

Learning activity knowledge rule. The learning activity knowledge rules discovered from data mining represents the associations of a learning activity's features and context characteristics, the rule format is shown as (6).

$$[feature_p \ldots \text{and } context_q \ldots] \rightarrow [feature_r] \quad [Support = s\%, Confidence = c\%] \tag{6}$$

1) Specific learning activity knowledge rule. Association rule mining was used to discover the hidden knowledge rule from context features and attributes. The knowledge rules of a specific learning activity assisted in realizing its purpose and working features. For example, [*Teacher03*, *Classroom05*] → [*Programming*] indicated that *Teacher03* in *Classroom05* was frequently associated with the *Programming* course.

2) Cross-learning activities knowledge rule. This work used sequential pattern mining to discover the hidden knowledge rule across-learning activities. The cross-learning activity knowledge rule assisted in realizing the association between different learning activities, e.g., [*Programming*, *WebService*] → [*NetworkManagement*] indicated that the *Programming* and *Web Service* courses in the current learning context were frequently associated with the *Network Management* course.

3) Cross-learning activities context knowledge rule. Sequential pattern mining was used to discover the hidden knowledge rule from context information cross-learning activities. Knowledge rules of context information of cross-learning activities assisted in realizing the context information association between different learning activities, e.g., [*Programming.ObjectOriented*, *WebService.WSDL*] → [*NetworkManagement.SOAP*] indicated that *Programming* course's *Object-Oriented concept* and *Web Service* course's *WSDL* were frequently associated with the *Network Management* course's *SOAP* in the current learning context.

Inferred learning activity features are considered as the Inferred knowledge. Then the inferred knowledge assists CBR in learning activity identification. Let F_j be the set of learning activity features of C_j that are collected by the system or inferred by the learning activity knowledge rules. A feature vector $\vec{C}_{Fj}$ is created to represent C_j. The weight of a feature fi in $\vec{C}_{Fj}$ is defined by (7).

$$w(f_i, C_j) = \begin{cases} CF_i & if\ f_i \in F_j \\ 0 & otherwise \end{cases} \tag{7}$$

If the f_i is inferred by the learning activity knowledge rules, $w(f_i, C_j)$ is set as CF_i - the inferred CF value of f_i ; if the f_i is selected by the user or gathered by the system, CF_i is set to value "1"; otherwise $w(f_i, C_j)$ is 0. Eq. 8 defines the similarity value $sim^F(C_k, C_j)$ of two learning activity cases C_k and C_j based on their learning activity features. The similarity value is derived by computing the cosine value of the feature vectors of C_k and C_j.

$$sim^F(C_k, C_j) = \text{cosine}(\vec{C}_{Fk}, \vec{C}_{Fj}) = \frac{\vec{C}_{Fk} \bullet \vec{C}_{Fj}}{|\vec{C}_{Fk}||\vec{C}_{Fj}|} \tag{8}$$

Similarity function for case-based reasoning. Equation (9) defines the similarity function used to compute the similarity measure between two cases C_k and C_j. The similarity function is modified by considering the combination of the similarity of text descriptions, attribute values and learning activity features.

$$similarity(C_k, C_j) = w_T sim^T(C_k, C_j) + w_F sim^F(C_k, C_j) + \sum_{x=1}^{m} w_x sim^A(C_k(attrb_x), C_j(attrb_x)) \tag{9}$$

where $sim^T(C_k, C_j)$ is the similarity value derived from the identifying term vectors of C_k and C_j; $sim^F(C_k, C_j)$ is the similarity value derived from learning activity features of C_k and C_j; $sim^A(C_k\ (attrb_x), C_j\ (attrb_x))$ is the similarity value obtained from the values of attribute x; w_T is the weight factor for the text description; w_F is the weight factor for the learning activity feature; and w_x is the weight given to attribute x. Note that the summation of w_T , w_F and all w_x is equal to 1.

Case-based reasoning for a target case. A target case is a learning activity that a student is currently studying. After entering a target case C_k of a learning activity, the system identifies an existing case identifier of C_k or retrieves similar learning activity cases if C_k is a new case. The similarity measures between the target case and previous cases are computed using (9). Assume there are n learning activity identifiers. Let $minsim(C_k, S_i)$ be the *minimum similarity*(C_k, C_j) over all C_j transformed into S_i. The procedure finds a learning activity identifier S_f such that $minsim(C_k, S_f)$ is the *maximum of* $minsim(C_k, S_i)$ over all S_i (for i = 1 to r). An existing learning activity identifier S_f is identified if $minsim(C_k, S_f)$ is greater than θ; otherwise, the learning activity is a new case and the system assigns a new identifier to it. The case and its identifier are then stored in the knowledge base, and *CBR* is initiated to retrieve similar cases based on their similarity measures and to suggest possible knowledge related to similar cases.

V. Adaptive Knowledge Support for Effective Learning

The system recommends/retrieves relevant knowledge documents to help students solve learning problem(s) based on learning activity profiles. The key contents of a codified knowledge document are represented as a term vector. The learning activity profile of a case C_S is expressed as a profiling term vector $\vec{p}_s$. The cosine measure of term vectors is used to derive the similarity measure. Let $\vec{d}_j$ be the term vector of document d_j. The cosine measure of $\vec{p}_s$ and $\vec{d}_j$, cosine ($\vec{p}_s$, $\vec{d}_j$), is the similarity measure between the learning activity and document d_j. Documents with the *top-N* similarity measures are selected as relevant documents.

The knowledge recommendation module suggests relevant documents according to the learning activity profile of the current learning activity or similar cases. Note that the *top-N* relevant documents are recommended according to the cosine measure of the term vectors of the documents and the learning activity profiles.

Besides, the learning activity profiles and relevant knowledge document sets are also integrated as the context-knowledge view. When a student's learning status indicates problems in a specific learning context, the system adaptively suggests supporting documents based on its profile as well as the corresponding context-knowledge view. For example, when a *CS* student does a study project, the system discovers knowledge document sets for the learning activity, including system analysis and design, programming, database management, network management, etc. The relevant knowledge documents for each learning activity include teaching material, questions and answers, concept identification, references, and tests. Besides, depending on the context-knowledge view, relevant knowledge documents on project paragon, project games, project demonstrations, which include project scope, menu of system analysis and design, menu of system operations, presentation slides, presentation report, etc. are also collected.

VI. Prototype System Demostration

A prototype system was developed to demonstrate the effectiveness of the proposed knowledge support system for effective learning. The implementation was conducted using several software tools, including Windows XP, PHP, and Adobe Dreamweaver CS4. A web and application server was set up on WampServer 2*i*, and MySQL was used as the database system for storing data related to the learning activities and codified knowledge documents. The data mining tool Weka 3.6 was used to discover knowledge rules in e-portfolio records.

Figure 2. Prototype knowledge support system

Fig. 2 illustrates the system interface. When a student logs into the system, the system adapts by showing active learning activities in the current learning context based on student's learning activity profiles. The system interface presents the learning activity context rules. For example, the rule: [*Object-oriented programming* (*OOP*, 程式設計) in First Semester (一上), *Database management system* (*DB*, 資料庫管理系統) in Second Semester (一下)] → [*Data mining* (*DM*, 資料探勘) in Third Semester (二上)], indicating *OOP* and *DB* learning activities in the current learning context is frequently associated with *DM* learning activity. Besides, the associations between the context features of learning activities are also illustrated in this interface, e.g., *DB.ch9_1* → *OOP.ch2*, the keyword is *UML*, and the score is *5*.

Figure 3. Knowledge acquisition from learning activity context rules

Fig. 3 illustrates the knowledge acquisition from learning activity context rules of a specific learning context. The system functions allow a student to get knowledge documents based on learning activity context rules in current learning context. According to the learning activity context rules, the student downloads various types of knowledge documents recommended by the proposed system. The score mechanism (我要評分) was also designed for students to get feedback in order to tune the accuracy of recommended knowledge.

VII. Conclusion

In this work, a novel knowledge support framework for learning context in the case of an abnormal status in an e-portfolio platform is proposed. Association rule and sequential pattern mining are used to discover context knowledge rules and patterns from existing e-portfolio records. The discovered rules identify frequent associations between context information and learning activity features. The discovered patterns indicate frequent associations between cross-learning activities. Discovered knowledge rules and patterns are used to construct context-knowledge views. Each specific learning context has its corresponding context-knowledge view. Case-based reasoning can then be employed to identify similar learning contexts. Moreover, information retrieval techniques are employed to extract learning activity profiles to model students' information needs in a certain context. Adaptive knowledge support can thus be facilitated by providing the student with learning activity-relevant information based on the profiles and corresponding context-knowledge view.

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