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Knowledge maps for composite e-services: A mining-based system platform coupling with recommendations

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Abstract

Providing various e-services on the Internet by enterprises is an important trend in e-business. Composite e-services, which consist of various e-services provided by different e-service providers, are complex processes that require the cooperation among cross-organizational e-service providers. The flexibility and success of e-business depend on effective knowledge support to access related information resources of composite e-services. Thus, providing effective knowledge support for accessing composite e-services is a challenging task. This work proposes a knowledge map platform to provide an effective knowledge support for utilizing composite e-services. A data mining approach is applied to extract knowledge patterns from the usage records of composite e-services. Based on the mining result, topic maps are employed to construct the knowledge map. Meanwhile, the proposed knowledge map is integrated with recommendation capability to generate recommendations for composite e-services via data mining and collaborative filtering techniques. A prototype system is implemented to demonstrate the proposed platform. The proposed knowledge map enhanced with recommendation capability can provide users customized decision support to effectively utilize composite e-services.

Keywords: Composite e-service; Knowledge maps; Topic maps; Data mining; Recommendation

1. Introduction

With the explosive growth of Internet, more enterprises are providing various e-services for collaborative commerce online to achieve competitive advantages. A complete service normally consists of various e-services, so by providing individual e-service online will not satisfy customer's demands. Composite e-services, which consist of various e-services provided by different e-service providers, are more attractable to serve customers. Composite e-services are complex processes that require the cooperation among cross-organizational e-service providers. In such complex collaborative commerce environments, online users face the difficulty of how to select the appropriate composite e-services that suit their needs. Accordingly, an effective knowledge support system is essential to organize and access related information resources in e-service environments.

Many researches have focused on the dynamic composition of e-services and system platforms to provide composite e-services (Balakrishnan, 2000; Casati and Shan, 2001; Piccinelli et al., 2001; Piccinelli and Williams, 2003), but very few researches consider managing information resources of composite e-services. Casati and Shan (2001) proposed a model to compose e-services dynamically. Balakrishnan (2000) proposed a Service Framework Specification to compose e-services. Several e-service platforms are proposed. For example, Hewlett-Packard e-speak and Microsoft.Net are such platforms that share many concepts and features. Basic features of these platforms are registering, advertising, monitoring, and managing e-services. However, conventional e-service platforms do not provide effective knowledge support for managing and accessing information resources of composite e-services.

Enterprises employ information technologies (ITs) to reuse valuable knowledge assets and carry out knowledge

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management activities (Davenport and Prusak, 1998; Liebowitz, 1999). Knowledge repository and knowledge maps are widely used ITs to support knowledge storage, organization and dissemination. A knowledge map is a visual display of captured information and relationships, which enables efficient communication and learning of knowledge (Vail, 1999). Knowledge maps have been used by enterprises to manage and navigate enterprises' explicit knowledge (Chung, Chen, and Nunamaker, 2003; Eppler et al., 2001; Gordon, 2000; Kim, Suh, and Hwang, 2003). Accordingly, this work proposes a mining-based knowledge map platform to provide effective knowledge supports for utilizing information resources of composite e-services.

A data mining approach is employed to extract knowledge patterns from the usage records of composite e-services. The extracted knowledge patterns, which represent the important subjects and associations of composite e-services, form the kernel of the knowledge map. Moreover, e-service providers may use different types of system platform, making it difficult to communicate and exchange information resources. Thus, a topic map standard (ISO) was adopted to develop the proposed knowledge map, providing a bridge for managing and exchanging heterogeneous resources of composite e-services. Meanwhile, the proposed knowledge map is integrated with recommendation capability to generate recommendations of composite e-services via data mining and collaborative filtering techniques. Finally, a prototype system was developed to demonstrate the operations of the knowledge map for browsing information resources of composite e-services as well as the recommendations. The proposed knowledge map enhanced with recommendations can provide users customized decision support to effectively utilize composite e-services.

The rest of this paper is organized as follows; Section 2 introduces related work. Section 3 describes the system framework of the proposed knowledge map for composite e-services. The architecture and functionality of the system are illustrated in Section 4. Section 5 presents the integration of recommendations in the system. Section 6 demonstrates the prototype system. Conclusions and future works are finally made in Section 7.

2. Related work

The related literatures include e-service, web service standards, knowledge maps, topic maps standards, recommendation approaches, and data mining techniques.

2.1. E-service platforms and Web service standards

Akhil, Vijay, and Klaus (2000) defines e-services as modular and agile electronic services that can perform work, achieve tasks or complete transactions. *Web service* is another term that is used to define the services provided via the Internet (Curbera et al., 2002). Web services and e-services are similar but Web services place an emphasis on Web technologies. Web services have been used to integrate business processes (Papazoglou et al., 2002). E-speak is an open software platform designed specifically for the development, deployment and intelligent interaction of e-services (Hewlett-Packard). Websphere Application Server is a Web service platform designed by IBM to implement and deploy Web services. XML has been widely used in electronic commerce, as it uses a flexible, open, and standard-based format to provide interoperability of data exchange over the Internet. Universal description, discovery and integration (UDDI), Web services description language (WSDL), and Simple Object Access Protocol (SOAP), have been accepted as the de facto standards for Web services (Tsalgatidou and Pilioura, 2002). UDDI provides directory services for registering and searching e-services. SOAP is an XML-based protocol for exchanging request/response messages between e-services providers and customers. WSDL is a XML-based language used to describe the usage (behavior) of e-services. Detailed introductions of these standards can be found in Curbera et al. (2002) and Tsalgatidou and Pilioura (2002).

2.2. Composite e-service platforms

Composite e-services are composed of several e-services, and, intuitively, it can be seen as a workflow. A workflow is an automated business process that manages the sequence of work activities and the use of appropriate human or IT resources associated with the various activity steps. Casati and Shan proposed a dynamic model for composing e-services (Casati and Shan, 2001; Casati and Shan, 2001). A composite service description language (CSDL) is designed to describe the composition of e-services by means of a directed graph. Piccinelli and Williams (2003) presented a Dynamic Service Composition (DySCo) infrastructure that uses a workflow model as a basis for composing Web services. Moreover, a composite e-service platform enhanced with recommendation ability has been proposed by Liu, Shen, and Liao (2003).

Some vendor protocols for constructing composite e-services are available, such as IBM's Web Service Flow Language (WSFL) and Micorsoft's XLANG. Recently, IBM, Microsoft, and BEA Systems merged their flow languages into "Business Process Execution Language for Web Services (BPEL4WS)" protocol (BPEL4WS and Process Execution Language for Web Services).

2.3. Knowledge maps

Successive knowledge map applications take advantages of the nature of visualization and navigation in locating and publishing knowledge (Davenport and Prusak, 1998). Vail (1999) highlighted the visual display of captured information. Chung et al. (2003) proposed a knowledge map framework for discovering business intelligence to alleviate information overload on the Web. Lin and Hsueh (2003) applied information retrieval algorithms to generate and maintain a knowledge map for virtual communities of practice. Kim et al. (2003) proposed a road map to develop knowledge maps in the industrial community. Moreover, Gordon (2000) exploited learning dependency to create knowledge maps.

2.4. Topic maps and XTM

The ISO standard ISO/IEC 13250 Topic map defines a model for the semantic structuring of link networks (ISO). Topic maps provide a bridge between the domains of knowledge representation and information management and link them to existing information resources (Rath and Pepper, 1999). The basic concepts are shown as following.

- Topics correspond to the formal description of concepts or objects in the real world. An expressive topic name is helpful to understand an object or a concept. Topic types are naturally created to classify topics.
- Occurrences are the original information resource connected to the meaningful topic names. A topic is an abstract label, and the occurrences are substantial references.
- An association is formally a meaningful link that specifies a relationship among several topic names. These semantic association relationships help users understand the connections among topic names.

Topic map standardization can provide a clear structure in assisting an enterprise to organize knowledge from different information resources and to build a knowledge-sharing environment for users to gain knowledge. Topic maps are used to construct a navigable knowledge map of composite e-services.

XML topic maps (XTM) (TopicMaps.Org, XML Topic Maps (XTM) 1.0) specified by TopicMaps.Org is an abstract model that uses XML grammar to express Web-based topic maps. Tables 1 and 2 show the XTM syntax of <topic> and <association>, respectively. The <topic> element defines the name and occurrence characteristics of a single topic. The optional and repeatable <instanceOf> element specifies a class of which the <topic> is an instance. The <baseName> specifies a name characteristic of the topic. The <occurrence> element specifies information resources that are relevant to the topic. The <baseName> and <occurrence> elements are optional and repeatable.

Table 1
XTM syntax of topic

<table>
<tr><th>XTM syntax of <topic> Element</th></tr>
<tr><td><!ELEMENT topic (instanceOf*, subjectIdentity?, (baseName | occurrence) *) >
<!ATTLIST topic
id ID #REQUIRED >
<!ELEMENT baseName (scope?, baseNameString, variant*)>
<!ELEMENT occurrence (instanceOf?, scope? (resourceRef | resourceData)) ></td></tr>
</table>

Table 2
XTM syntax of association

<table>
<tr><th>XTM syntax of <association> Element</th></tr>
<tr><td><!ELEMENT association (instanceOf?, scope?, member+)>
<!ATTLIST association
id ID #IMPLIED >
<!ELEMENT member
(roleSpec?, (topicRef | resourceRef | subjectIndicatorRef)+) >
<!ELEMENT roleSpec (topicRef | subjectIndicatorRef) ></td></tr>
</table>

The <association> element specifies a relationship among topics that play roles as members of the association. The optional <instanceOf> element specifies the class to which an <association> belongs. The <member> element defines all topics that play a given role defined by the <roleSpec> element in an association. The <member> element is mandatory and repeatable.

2.5. Recommendations with collaborative filtering

Recommender systems are technologies that assist businesses to implement one-to-one marketing strategies. Various techniques have been proposed to implement recommender systems (Kim, Yum, Song, & Kim, 2005; Lee, Kim, & Rhee, 2001; Lee, Jun, Lee, & Kim, 2005 Yu, Liu, and Li, 2005). Collaborative filtering (CF) (Breese, Heckerman, and Kadie, 1998). has been successfully used in various applications. The CF method utilizes preference ratings given by various users to determine recommendations to a target user based on the opinions of other similar users. Users' preference ratings are used to compute correlation coefficients among users. The correlation coefficient (e.g. *pearson* correlation coefficient) is a measure of the similarity between two different users' preferences. The k Nearest Neighbors (k-NN) approach is often used to derive the neighborhood (similar users) of a user. The recommender system then generates recommendations based on the predictions derived from the preferences of the neighborhood. The GroupLens system (Konstan et al., 1997) applied the CF method to recommend Usenet News and movies. The video recommender (Hill, Stead, Rosenstein, and Furnas, 1995) also used the collaborative approach to generate recommendations on movies. Examples of music recommender systems are Ringo (Shardanand and Maes, 1995) and MRS (Chen and Chen, 2001).

2.6. Data mining

Data mining has become a research area with increasing importance. Data mining involves several tasks for different mining purposes, including association rule mining, clustering, classification, prediction, and time-series analysis (Chen, Park, and Yu, 1996; Han and Kamber, 2000). This work employs the clustering method and association rule mining to extract knowledge patterns from historical executions of composite e-service instances.

Clustering. Clustering is an unsupervised learning method that groups data to maximize similarity within each cluster and dissimilarity among different clusters. Well-known algorithms, such as Agglomerative, K-means, CURE, CHAMELEON, have been implemented in numerous applications (Han and Kamber, 2000). K-means (MacQueen, 1967) is a method commonly used to partition a set of data into K groups. The K-means algorithm assigns data samples to clusters by the minimum distance assignment principle, which assigns a data sample d_i to the cluster c_j such that the distance from d_i to the center of c_j is the minimum over all K clusters.

Association rule mining. Association rule mining aims to find an association between two sets of products in the transaction database. Agrawal, Imielinski, and Swami (1993) formalized the problem of finding association rules as follows. Let I be a set of product items and D be 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 herein. 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 of a rule is the fraction of transactions that contain X, also contain Y.

The support of an association rule indicates how frequently that rule applies to the data. Higher support of a rule corresponds to a stronger correlation between the product items. The *apriori* algorithm (Agrawal et al., 1993; Agrawal and Srikant, 1994) is typically used to find association rules by discovering frequent *itemsets* (sets of items). An *itemset* is considered to be frequent if the support of that *itemset* exceeds a user-specified minimum support. Association rules that meet a user-specified minimum confidence can be generated from the frequent *itemsets*.

3. System framework of knowledge map platform for composite e-services

The proposed knowledge map (Kmap) platform aims to add values to the composite e-services by providing users with the support of a knowledge map navigator and recommendations. The Kmap platform includes two main subsystems: a knowledge map system and a recommender system. Fig. 1 shows the system framework of the Kmap platform for composite e-services.

3.1. Knowledge map system

The knowledge map system includes four main modules, *service collecting* & *planning, data mining*, *topic maps generator*, and *navigator interface modules.*

- *Service collecting and planning module.* This module collects e-service information provided by various e-service providers. Predefined composite e-services are stored in

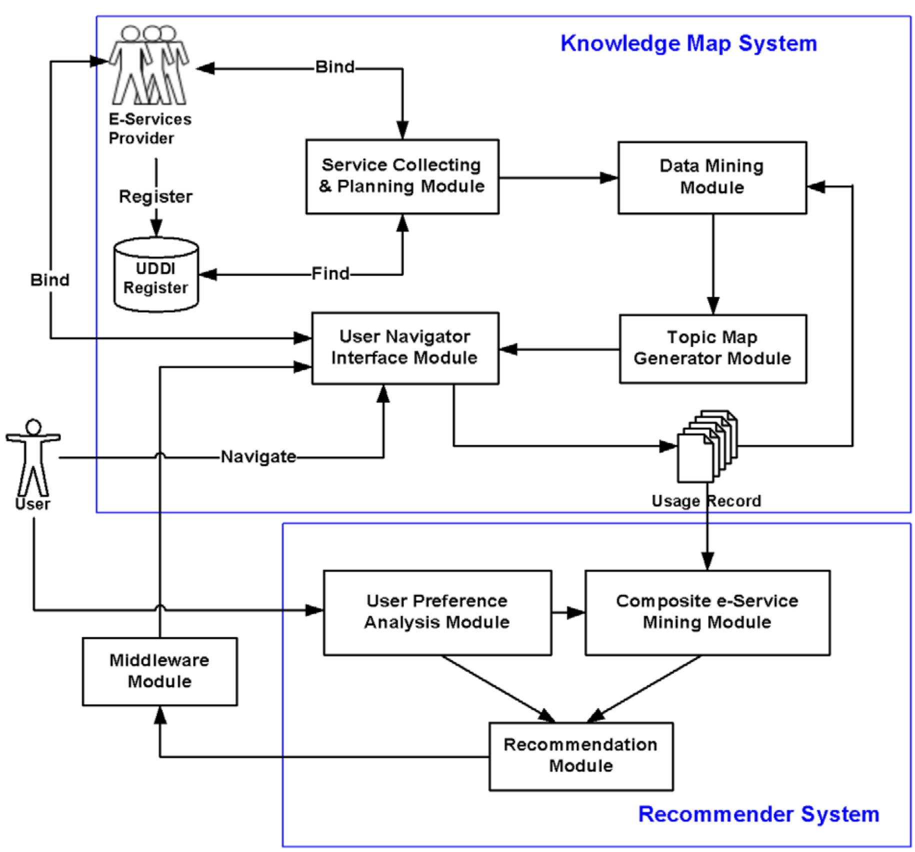


Fig. 1. The system framework of the Kmap platform.

the system. Moreover, the module generates service plan templates to assist users in sketching a composite e-service.

- *Data mining module.* Data mining techniques are employed to discover valuable knowledge patterns from usage records and meta-information of composite e-services. The usage records log the historical executions of composite e-services conducted by various users. Important subjects (topics) and their associations of composite e-services are discovered via clustering and association rule mining techniques.
- *Topic maps generator module.* To facilitate knowledge exchange and sharing, XTM (XML topic maps) were employed to construct the proposed knowledge map. The discovered knowledge patterns, including the valuable subjects and their associations, were used to form the topics and topic associations of the knowledge map.
- *User navigator interface module.* This module provides a navigator for the user to browse composite e-services and related knowledge patterns by using the XTM-based interface.

3.2. Recommender system

A composite e-service is composed of several e-services which can be seen as a workflow. Customers need to specify the ordering and attributes of selected (basic) e-services to define a composite e-service. Customers also need to choose an e-service provider for each selected e-services. The proposed Kmap system can recommend the frequent attributes of each basic e-service, the ordering between e-services, and the top N matching composite e-services that contain the desired e-services. Moreover, group-based recommendations are supported via analyzing the usage behaviors of interest-groups. Collaborative filtering is employed to recommend e-service providers for selected e-services.

The recommender system includes four main modules, *user preference analysis, composite e-service mining, composite e-service recommendation*, and *middleware modules.*

- *User preference analysis module.* This module uses the *pearson* correlation coefficient to compute the similarity between users based on user's preference ratings on e-services served by various providers. Users' feedbacks (ratings) about their preferences on e-services are collected in a customer-preference database. The *k-NN* approach is used to derive a user's neighborhood (similar users). Moreover, a clustering approach is employed to cluster customers into interest-groups based on similarity measures.
- *Composite e-service mining module*. This module uses the association rule mining approach to discover *frequent attributes* of each basic e-service and *frequent ordering* between e-services from the instance execution logs. Moreover, the mining can also be conducted via considering the usage records of interest-groups to discover frequent group-based attributes and orderings.
- *Composite e-service recommendation module.* A scoring approach is used to recommend the top N composite e-services according to the mining result. Group-based recommendations are achieved based on the mining result discovered from the usage records of interest-groups. Moreover, the collaborative filtering (CF) approach is used to recommend e-service providers for the selected e-services. The CF approach makes recommendations via considering the preferences of neighborhood (similar users).
- *Middleware module.* This module is a bridge between the knowledge map system and the recommender system. The middleware module delivers recommendations generated by the recommender system to the navigator, while the user is browsing the knowledge map. User identification is performed to extract recommendations for the target user. The recommendations are transformed into dynamic Web pages (such as JSP or ASP etc.) to provide customized decision support in the Kmap navigator.

4. Knowledge maps system

Fig. 2 shows the modules for deploying knowledge maps. This section introduces each module in the knowledge map system with details.

4.1. Service collecting and planning

The e-service providers deployed their e-services into Web services. The module provides WSDL documents of Web services to illustrate the services and functions provided in each Web service. E-service providers can register each Web service's access point and description information into the UDDI registry. The registered information includes: e-service provider information, e-service information, access point, and the connection with the technical model which is a part of WSDL documents. The service plan designer can search and collect the WSDL documents of each Web service through UDDI Registry. Based on the information provided in the WSDL documents, service plan designer can obtain information on the access point for a particular e-service provider. E-service and composite e-service information provided by the e-service provider are built into the service database. Service plan designer can design a composite e-service by composing different e-services registered in the database. Attributes of these e-services and composite e-services are important information resources in the data mining module for knowledge discovery.

4.2. Knowledge map template for composite e-service

Based on the information stored in the service database, attributes (meta information) of e-service and composite

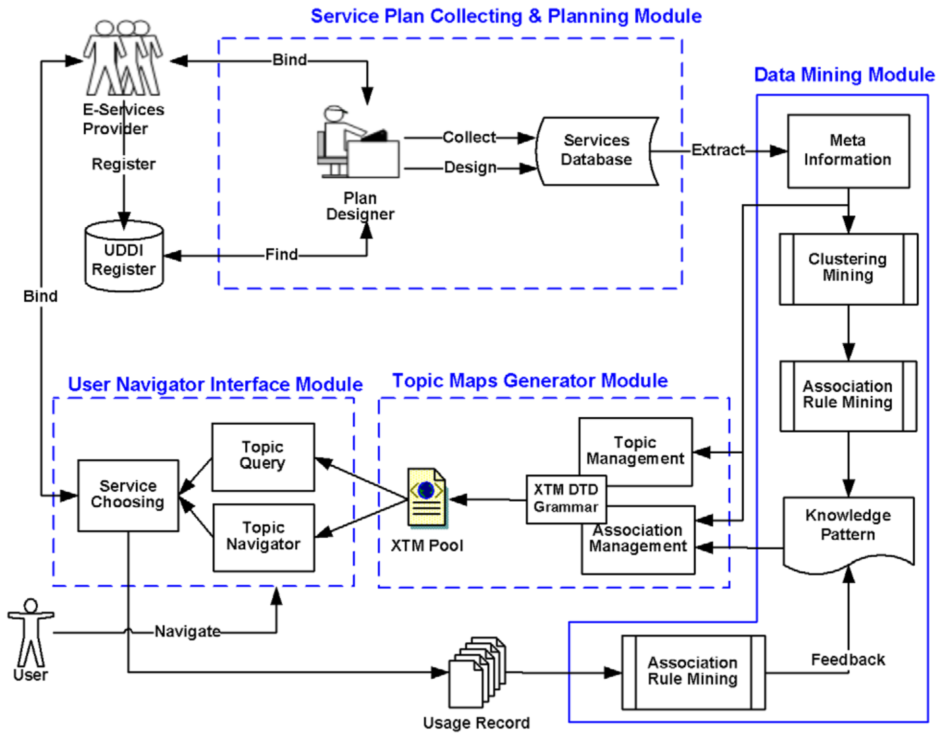


Fig. 2. Knowledge map system.

e-service are extracted for further discovery of knowledge patterns. Knowledge map templates are designed to record the discovered knowledge patterns.

4.2.1. Meta information for the composite e-service

Meta information is information about data which describes e-services and composite e-services. A composite e-service is a combination of several basic e-services. Thus, the meta information of a composite e-service also need to include the meta information of e-services. In a composite e-service, And-split (join) and Or-split (join) are included to control the flow and execution orders of basic e-services. For the remainder of this paper, we use training programs which contain a series of training-courses (e-services) as the examples of composite e-services to illustrate the proposed work. A training-course generally consists of the following attributes: course name, provider, category, difficulty, location, time period, instructor, hours, and cost. Table 3 shows the extracted meta information of a composite e-service "MCSD training program". Microsoft Certified Solution Developers (MCSD) is a certification of passing the exams for C programming, SQL server, and so on. The MCSD training program includes a series of training courses for taking MCSD exams.

4.2.2. Topic maps template

Knowledge map templates are used to record the discovered knowledge patterns and to further generate the knowledge map. We use the XML topic maps (XTM) (Topic Maps.Org, XML Topic Maps (XTM) 1.0) to construct the core structure of knowledge map templates. The topic types, association types and occurrences are used to express a composite e-service and related knowledge patterns. For example, e-service providers or attributes of e-services are termed as topics in XTM.

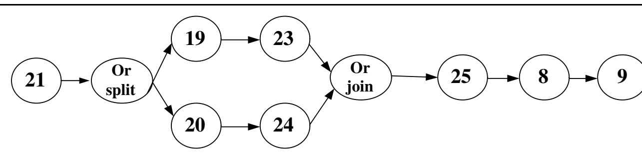
According to the meta information extracted from composite e-services, the general attributes for e-services are classified as follows – **ServiceName**: the name of an e-service; **Provider**: description of an e-service provider; **Category**: the category of an e-service; **Location**: location of an e-service; **Cost**: cost of an e-service; and **Rating**, satisfaction level of an e-service. Moreover, **ExtAttribute** can be used to define extendable attributes of specific e-service. In this work, extendable attributes of e-services corresponding to training courses consist of **Difficulty**, **Instructor**, **TimePeriod**, and **Hours**. Each class (e.g. Provider or Instructor) of the attributes is defined as a topic type in XTM. Each attribute corresponds to a topic with a defined topic type in XTM. For example, "Database" is a topic with topic type "Category".

Furthermore, several other topic types are defined as follows – **CS**: composite e-service; **BS**: basic e-service; **And-Split (join):** and-split (join) control flow in a composite e-service; **Or-Split (join):** or-split (join) control flow in a composite e-service; **Start:** starting node of a composite e-service; **Stop:** end node of a composite e-service.

The relationships among topics are defined as associations. Several types of associations are defined as follows – **Sequence:** ordering relationship among e-services; **Contain:** structural relationship between a composite e-service and

Table 3
Meta information of a composite e-service "MCSD training program"

ID	Service name	Provider	Category	…….	Hours	Cost
21	Developing Microsoft ASP.NET Web Applications Using Visual Studio .NET	Mitac	Programming	…….	24	12,000
19	Programming with C#	Mitac	Programming	…….	24	10,000
23	Developing Microsoft .NET Applications for Windows (C#)	Mitac	Programming	…….	28	15,000
20	Programming with Visual Basic.Net	Ucom	Programming	…….	24	10,000
24	Developing Microsoft .NET Applications for Windows (Visual Basic .NET)	Ucom	Programming	…….	24	15,000
25	Developing XML Web Services Using Microsoft ASP.NET	Mitac	Programming	…….	28	15,000
8	Administering a Microsoft SQL Server 2000 Database	Mitac	Database	…….	24	10,000
9	Programming a Microsoft SQL Server 2000 Database	Mitac	Database	…….	24	11,000
1001	**MCSD**	**{Mitac, Ucom}**	**{Programming, Database}**	…….	**152**	**73,000**



MCSD training program

its e-services. A topic may play a given role defined by the <roleSpec> element in an association. Two roles of the association "Sequence" are defined – StartPoint: the starting point; EndPoint: the end point. Two roles of the association "Contain" are defined – Parent: a composite e-service plays the role of Parent in the "contain" structure; Children: an e-service plays the role of Children in the "contain" structure. An e-service (a composite e-service) contains several attributes which can also be specified by the "Contain" association type. The e-service (composite e-service) plays the role of "Parent", while the attributes play the role of Children in the "contain" structure. An attribute is normally associated to one or more basic and composite e-services. The association type – **RelateTo** is defined to link associated e-services or composite e-services to an attribute. Moreover, an association type – **Relevance,** which denotes the relevance relationship between e-services or service attributes, is defined to record the association patterns discovered from the mining results, as shown in Table 4.

Table 4
An excerpt of XTM for association type "Relevance"

Relevance

```
<topic id="Relevance">
  <baseName>
    <baseNameString>Relevance</baseNameString>
    </baseName>
</topic>

<association id="R3">
  <instanceOf> <topicRef xlink:href="#Relevance"/></instanceOf>
  <member><topicRef xlink:href="#608"/> </member>
  <member><topicRef xlink:href="#622"/></member>
</association>
```

4.3. Discovering knowledge patterns

A two-phase data mining process is employed to discover valuable knowledge patterns from usage records and meta-information. The usage records log the historical executions of composite e-services conducted by various users. A clustering technique is used to group composite e-services based on the similarity measure derived from meta information. Important topics (attributes) of each cluster (group) are extracted to represent the meta information of each cluster. Association rule mining is then employed to discover attribute associations (relevant relationship) in each cluster. The topics and associations form the kernel of the Kmap system. The "Relevance" associations between topics are used to recommend relevant topics during the navigations of the knowledge map. Training-programs are used as the examples of composite e-services to explain the steps of knowledge discovery.

4.3.1. Clustering composite e-services

A composite e-service is a combination of basic e-services. The meta information of a composite e-service include the meta information of its basic e-services. The clustering assigns similar composite e-services into the same group. A basic e-service will also be assigned to the cluster where the composite e-service belongs. Notably, an e-service may be assigned to more than one group. The major steps of clustering are described as follows.

Transform meta information into vector model. As mentioned before, general attributes are classified into defined topic types. Each e-service's meta information can be transformed into values represented in a vector space model. For binary representation, all attributes included in an e-service are assigned a value of 1; 0, otherwise. A composite e-service's vector contains the meta information of a composite e-service and the union of all the vectors of basic e-services included in the composite e-service.

Calculate the dissimilarity between composite e-services. This work uses the Euclidean distance measurement to compute the proximity distance between pair-wise vectors.

Form clusters. The *K*-Means clustering technique is employed to perform clustering in which the Euclidean distance is used to measure the dissimilarity between composite e-services. A composite e-service cs_i is assigned to cluster C_j such that the dissimilarity measure between cs_i and the center of C_j is the minimum over all K clusters. Notably, the center of C_j is the vector derived by averaging over the vectors of composite e-services in C_j. The assignment process repeats until no new assignment can be found.

Determine the important topics of each cluster. A cluster centroid is extracted to represent the major attributes of a cluster of composite e-services. The frequently appearing attributes will form the cluster centroid. A vector model is also applied to represent a cluster centroid. If an attribute is present more often than the defined threshold value in a cluster, then this attribute is set to 1 in the centroid vector; otherwise, it is set to zero. The extracted important attributes of a cluster centroid form the topics in the discovered knowledge map of composite e-services. Moreover, hyperlinks are created to link each topic name to relevant references (occurrences).

4.3.2. Mining association patterns among service attributes

Mining association patterns is helpful to derive the practical rules, which could give users immediate decision-making support. This work employs the *apriori* algorithm to find association patterns, namely frequent topic sets satisfying minimum support, from the usage records and meta information of composite e-services within a cluster. Two kinds of association patterns are discovered: association patterns of basic e-services and association patterns among composite e-services. The discovered association patterns form the topic associations in XTM.

Association patterns of basic e-services. Such association patterns are discovered via applying association rule mining to the usage records (transaction set) of e-services in which an instance of e-service corresponds to a transaction. The association patterns mainly consist of associations between attributes which are derived from the frequent attribute sets of the mining result. Notably, an attribute-set (set of attributes), for example, {Instructor "Nancy", Difficulty "Basic"}, is considered to be frequent if the support of that attribute-set exceeds a system-specified minimum support. Each attribute corresponds to a topic with a defined topic type in XTM. For example, "Nancy" is a topic with topic type "Instructor". The associations among several types of attributes can be discovered. To simplify the discussion, we use frequent attribute-sets of size 2 as examples to describe the discovered association patterns. The association: Instructor "Nancy" ↔ Difficulty "Basic" implies that the instructor "Nancy" often lectures on courses with "Basic" difficulty; The association: Provider "Mitac" ↔ Category "Database" implies that users often take training courses of "Database" category provided by the Provider "Mitac"; The association: ServiceName "Programming with C#" ↔ Provider "Mitac" implies that users often take the training course "Programming with C#" provided by the Provider "Mitac".

Association patterns among composite e-services. Such association patterns are discovered via applying association rule mining to the usage records (transaction set) of composite e-services in which an instance of composite e-service corresponds to a transaction. The association patterns mainly consist of associations between attributes or e-services which are derived from the frequent attribute sets of the mining result. Notably, an e-service is represented by its service name. The associations among several types of attributes can be discovered. The association: Category "Programming" ↔ Category "Database" implies that the Category "Programming" and the Category "Database" are often included in a training program (composite e-services). The association: Provider "Mitac" ↔ Provider "Ucom" implies that users often take a training program including courses provided by the Provider "Mitac" and "Ucom"; The association: ServiceName "Programming with VB .Net" ↔ ServiceName "Programming a MS SQL Server 2000 Database" implies that the courses "Programming with VB .Net" and "Programming a MS SQL Server 2000 Database" are often included in a training program.

4.3.3. Recommendations based on association patterns

The association patterns imply the relevance relationships between topics, and can be used to recommend relevant topics during users' navigations of the knowledge map. For example, the system suggests that the user can choose the course "Programming a MS SQL Server 2000 Database", when the user has already selected the course "Programming with VB .Net" according to the association pattern: ServiceName "Programming with VB .Net" ↔ ServiceName "Programming a MS SQL Server 2000 Database".

4.4. Topic maps generator

This module generates the knowledge map of composite e-services in XTM documents based on the mining results. The important attributes of basic and composite e-services extracted from each cluster form the topics in XTM. Association patterns discovered from association rule mining form the topic associations. Moreover, the module generates XTM for a composite e-service according to the association types "Contain" and "Sequence" described in Section 4.2.2.

4.4.1. Topic management

Service names and attributes of basic and composite e-services are the topics in the XTM structure. Each topic belongs to a topic type and is an instance of the topic type. For example, the attribute “Database” is a topic of the topic type “Category”.

4.4.2. Composite e-service in XTM

A composite e-service contains several basic e-services. The association type “contain” with the role of parent or children is defined to express the structural relationship under the XTM format. The parent role represents the composite e-service. The child role represents the basic e-service. Table 5 shows the XTM format where a composite e-service “MCSD” (#1001) contains an e-service “Programming with C#” (#19).

A composite e-service consists of one or more service flows which can be represented as a sequence. In the XTM format, association type of “Sequence” is used to represent the orders of the flow sequence. StartPoint represents the beginning node and EndPoint represents the end node in the composite e-service. Fig. 3 shows the XTM format for the flow of a composite e-service.

Table 5
An excerpt of XTM for association type “Contain”

```
<topic id=”Contain”>
  <baseName> <baseNameString>Contain</baseNameString>
  </baseName>
</topic>

<association id=“MCSD_C1”>
  <instanceOf><topicRef xlink:href=”#Contain”/></instanceOf>
  <member>
    <roleSpec><topicRef xlink:href=”#Parent”/></roleSpec>
    <topicRef xlink:href=”#1001”/></member>
<member>
    <roleSpec><topicRef xlink:href=”#Children”/></roleSpec>
    <topicRef xlink:href=”#19 “/></member>
</association>
```

4.4.3. Association management

The association type “Relevance” described in Section 4.2.2 is used to record the association patterns discovered from the mining results. The association type represents the relevance relationship between e-services or service attributes. The discovered association patterns can be classified into the following classes.

Class 1: Association patterns of basic e-services.

This class of association patterns are discovered via applying association rule mining to the usage records (transaction set) of e-services. The association patterns mainly consist of associations between attributes which are derived from the frequent attribute sets of the mining result. Several kinds of attribute associations can be discovered via association rule mining, as described in Section 4.3.2. Table 6 shows an association pattern indicating that

Table 6
XTM format of association between “Taipei” and “Nancy”

```
<topic id=“608”>
    <instanceOf> <topicRef xlink:href=”#Location”/>
    </instanceOf>
    <baseName> <baseNameString>Taipei</baseNameString>
    </baseName> . . . . . . . . . .
</topic>
<topic id=“622”>
    <instanceOf> <topicRef xlink:href=”#Instructor”/>
    </instanceOf>
     <baseName><baseNameString>Nancy</baseNameString>
    </baseName> . . . . . . . . . .
</topic>

<association id=“R3”>
     <instanceOf> <topicRef xlink:href=”#Relevance”/>
   </instanceOf>
     <member> <topicRef xlink:href=”#608”/> </member>
     <member> <topicRef xlink:href=”#622”/> </member>
</association>
```

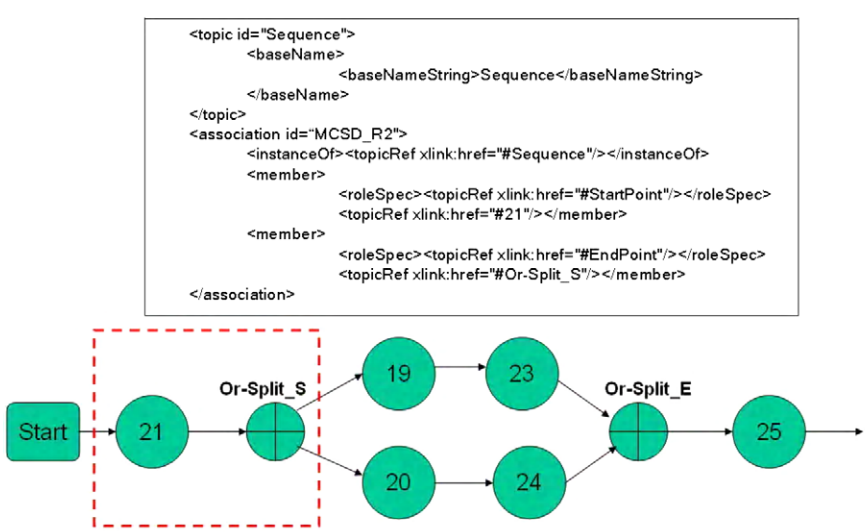


Fig. 3. XTM format of a composite e-service – MCSD.

Table 7
XTM format of association between e-services (course 9 and 19)

```
<topic id="9">
  <instanceOf><topicRef xlink:href="#BS"/></instanceOf>
  <baseName>
    <baseNameString> Programming a Microsoft SQL Server 2000
  Database </baseNameString>
  </baseName> ...............
</topic>
<topic id="19">
  <instanceOf><topicRef xlink:href="#BS"/></instanceOf>
    <baseName>
      <baseNameString>Programming with C#</baseNameString>
  </baseName>...............
</topic>

<association id="R5">
  <instanceOf><topicRef xlink:href="#Relevance"/></instanceOf>
    <member>
      <topicRef xlink:href="#9"/></member>
    <member>
      <topicRef xlink:href="#19"/></member>
</association>
```

the attribute instructor “Nancy” is relevant to the location “Taipei”, implying that users often take training courses at location “Taipei” with instructor “Nancy”.

Class 2: Association patterns among composite e-services. This class of association patterns are discovered via applying association rule mining to the usage records (transaction set) of composite e-services. The association patterns mainly consist of associations between attributes or e-services which are derived from the frequent attribute sets of the mining result. The associations among several types of attributes or e-services (service names) can be discovered, as described in Section 4.3.2. Table 7 shows an association pattern describing the relevance relationship between e-services. The example shows that the e-service “Programming a MS SQL Server 2000 Database” (course 9) is relevant to the e-service “Programming with C#” (course 19), implying that the courses “Programming a MS SQL Server 2000 Database” and “Programming with C#” are often included in a training program (composite e-service).

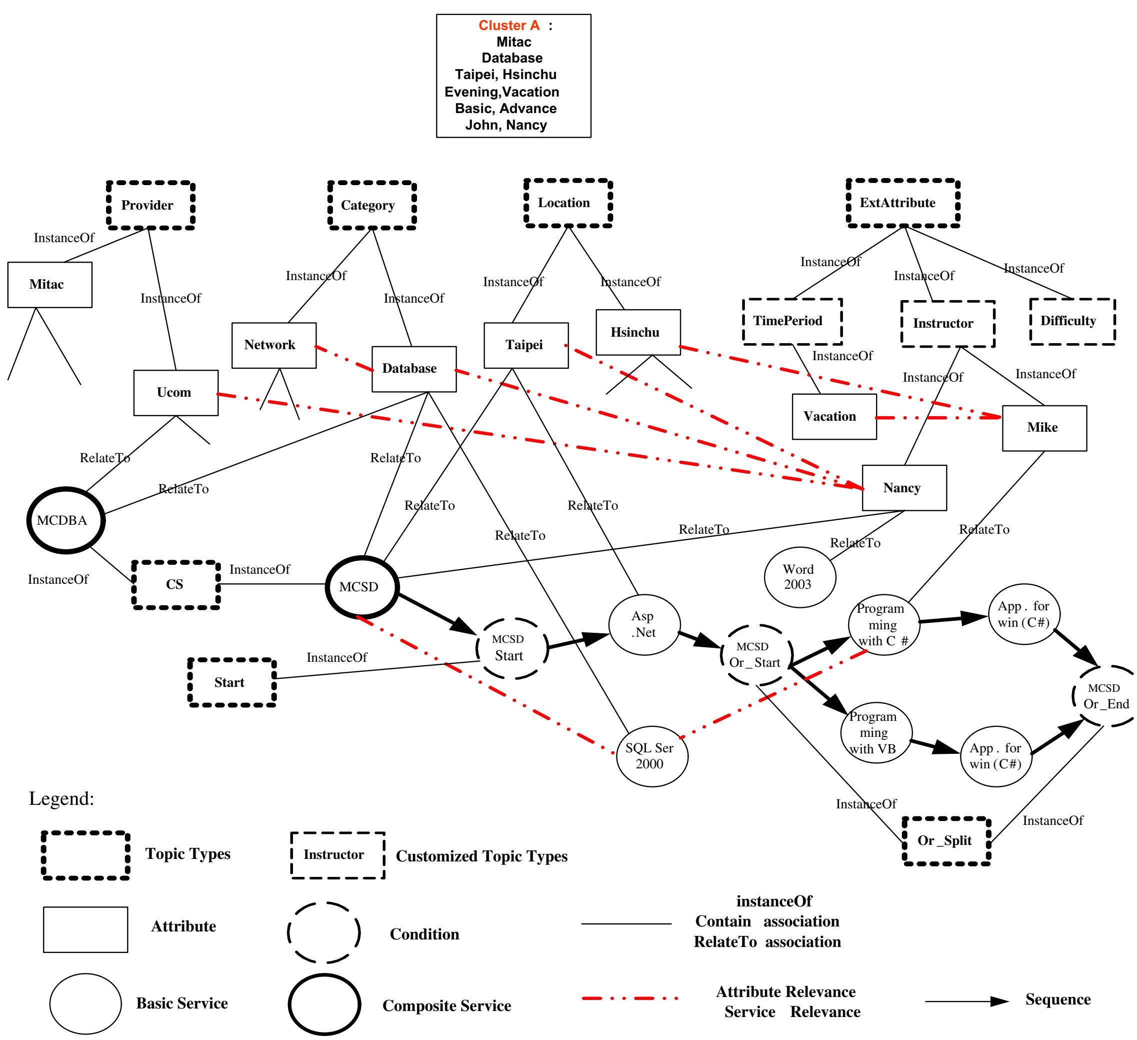


Fig. 4. Knowledge map diagram of Cluster A.

4.5. User navigator interface

This module provides an XTM-based navigator for the user to browse composite e-services and related knowledge patterns. This module consists of three main functions:

- *Topic navigator:* Users can navigate composite e-services, through extracted topics and association patterns of each cluster. The relevance relationships between topics are used to recommend relevant topics during users' navigations. The system assists users to find useful information of composite e-services through topics and associations organized in XTM.
- *Topic search:* The Kmap platform consists of a search interface which can assist users to find requested topic through keyword search.
- *Service selection:* After users select an e-service, the Kmap platform will connect the user to the e-service provider's Web service system, providing detailed information of the chosen e-service.

Topic maps navigation. Fig. 4 shows a part of the constructed knowledge map for a cluster A. The major attributes of the cluster are shown in the top of the figure. The topics and associations are also shown in the figure. For example, the attribute "Nancy" is an instance of topic type "Instructor" which is a customized topic type; "Nancy" is related to "Word 2003" by the "RelateTo" association which is a type of associations between attributes and e-services (composite-e-services). Nancy is relevant to the attribute "Database" by the "Relevant" association which is a type of associations between attributes. An e-service "SQL server 2000" is relevant to the e-service "Programming with C#" according to association pattern discovered from the usage records of composite e-services; indicating that "SQL server 2000" and "Programming with C#" are often selected in a composite e-service. A composite e-service "MCSD" contains several e-services (e.g. Asp .Net, Programming with C#) ordered by the "Sequence" and "Or/And-split/join" operators.

When a user browses the Cluster-A section, the navigator lists the extracted topic types and topics of cluster A. Assume a user browses the topic "Location → Taipei", the navigator will display the related training courses (e.g. Asp .Net) located in Taipei city, through the "RelateTo" links. The navigator will also display the relevant attribute "Nancy" according to the "Relevant" association. When a user browses a certain e-service, the navigator can suggest relevant e-services through the "Relevant" association. Further recommendations can also be provided to suggest frequent attributes of e-services, frequent used e-services and frequent ordering among e-services. The Kmap platform also provides advanced recommendations including recommending the provider of e-services and recommending composite e-services. The details are illustrated in Section 5.

5. Recommender system

The recommender system implements two approaches to generate recommendations: collaborative filtering and association rule mining. Our previous study (Liu et al., 2003) recommended composite e-services without considering interest-groups. This work extends our previous study by considering interest-groups to provide group-based recommendations. Customer interest-groups are derived according to the users' ratings on the usage of e-services served by various providers. Group-based recommendations to a target user u can be conducted based on the frequent behaviors of customers in the same interest group with u. Moreover, our previous work (Liu et al., 2003) focuses only on recommending composite e-services, thus recommending e-service providers is further proposed in Section 5.3.4. Fig. 5 shows the proposed recommendation process.

The proposed Kmap system can recommend the frequent attributes of each basic e-service, the frequent ordering among e-services, and the top-N composite e-services that contain desired e-services. Furthermore, collaborative filtering is employed to recommending e-service providers for selected e-services. The flow schema database stores the existing composite e-service definitions. The instance execution log database contains usage records of composite e-services which records historical instance executions of flow schema. A flow schema may be instanced several times.

5.1. User preference analysis

After conducting a specific e-service served by an e-service provider, users are asked to evaluate the e-service. Users' feedbacks (preference ratings) on e-services served by various providers are collected in the Kmap system. The *Pearson* correlation coefficient is used to identify each user's similarity toward other users based on users' preference ratings. Similarity between users is calculated via

$$w(u,i) = \frac{\sum_{j \in I_{ui}} (r_{u,j} - \overline{r_u})(r_{i,j} - \overline{r_i})}{\sqrt{\sum_{j \in I_{ui}} (r_{u,j} - \overline{r_u})^2} \sqrt{\sum_{j \in I_{ui}} (r_{i,j} - \overline{r_i})^2}} \tag{1}$$

where $w(u,i)$ is the similarity between an active user u (whom we want to recommend to) and user i; $r_{u,j}$,$(r_{i,j})$ is the rating of user $u(i)$ for item j; $\overline{r_u}, \overline{r_i}$ is the average rating of user u (i); and I_{ui} is the set of items that were rated by both user u and user i; each item denotes a specific e-service served by an e-service provider.

Identifying neighborhood. The *k-NN* (nearest neighbor) approach is used to select the neighborhood. Users are ranked by their similarity measures in relation to the target user u,as determined using the *Pearson* correlation coefficient. The $k$most similar users are selected as the k-nearest neighbors of u.

Forming interest-group. K-means approach is used to cluster users into interest-groups based on the similarity measures derived by Eq. (1). The K-means algorithm

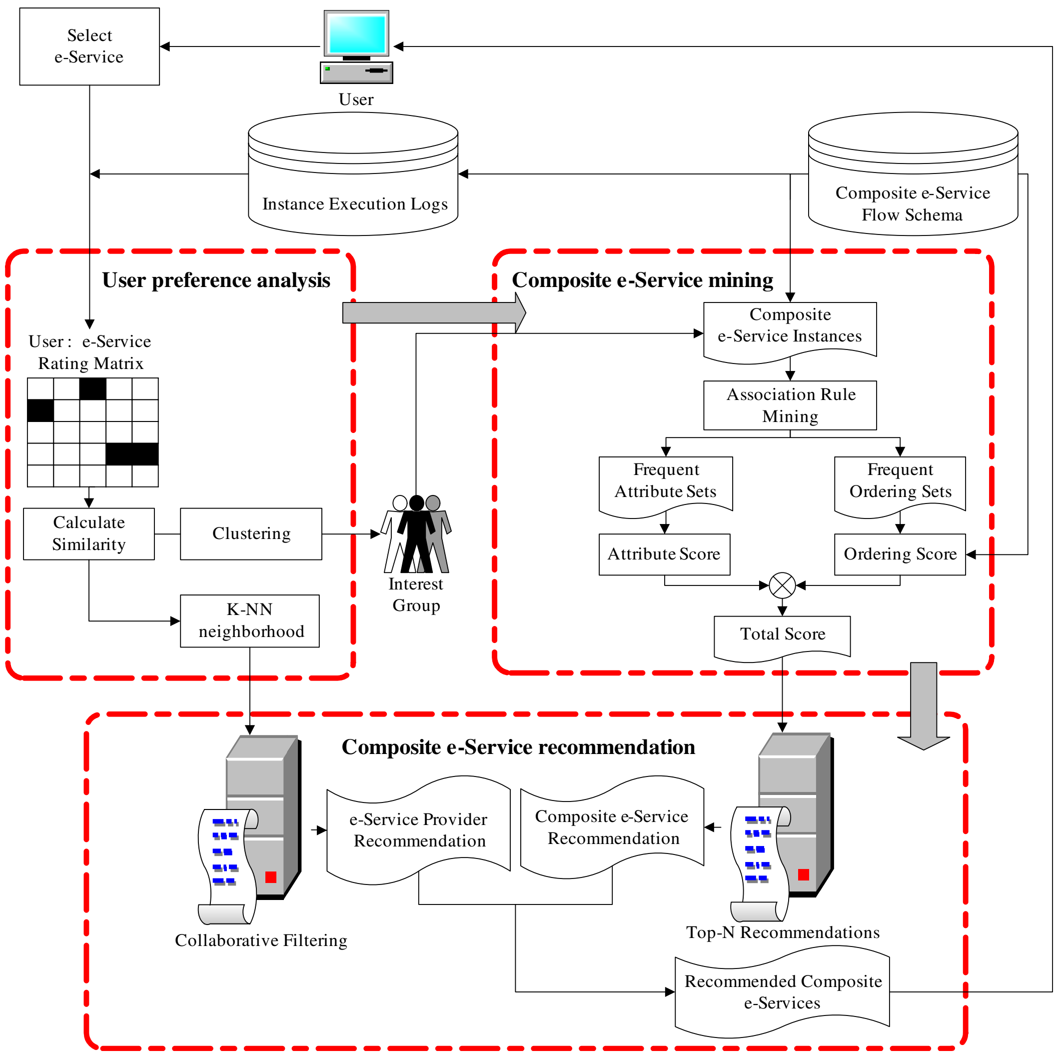


Fig. 5. Recommender system.

assigns a customer u_i to the cluster c_j such that the similarity measure between u_i and the center of c_j is the maximum over all K clusters.

5.2. Composite e-service mining

Composite e-service is a composition of various individual e-services. This module mainly discovers frequent orderings between e-services and frequent attributes of basic e-services. The frequent attributes of basic e-services are termed as frequent attribute sets in this work. The frequent orderings between e-services are termed as frequent ordering sets. Moreover, the mining can also be applied to the instance execution logs of interest-groups to discover frequent group-based attribute sets and ordering sets.

Mining frequent ordering sets. The *ordering* between e-services x and y, denoted by $\langle x, y\rangle$, means that x precedes y in the composite e-services. A set of ordering list can be derived from each instance of composite e-service. Every element $\langle x, y\rangle$ in the ordering list is a candidate item for deriving frequent ordering sets. The support of an ordering set OS is the ratio of instances that contain all orderings in OS. Ordering sets with support values greater than the required minimum support values are called frequent ordering sets. The *apriori* algorithm is used to generate the frequent ordering sets that satisfy the required minimum support value.

Mining frequent attribute sets. The *apriori* algorithm is also used to discover the frequent attribute sets. The support value of the attribute set is the ratio of those instances that contain all attributes in the attribute set. Attribute sets with support values greater than the minimum support value are called frequent attribute sets.

5.3. Recommendations

5.3.1. Basic recommendations

Assume a user wants to plan a new training program (composite e-service). He may select several training courses from the service pool. For example, the user selects the course “SQL server”, “Programming with C#”, “ASP .NET”, and “Database management”. The proposed system can recommend the frequent attributes and orderings of these e-services according to the mining results.

5.3.2. Composite e-service recommendations

Basic recommendations cannot suggest a complete flow of composite e-services. A user needs advanced recommendations about complete composite e-services. Our previous study (Liu et al., 2003) proposed a scoring approach to provide the recommendations of composite e-services. The following summarizes the scoring approach. The Flow Schema Database records the existing composite e-service definitions. We first extract the composite e-services that include the selected e-services. Two scores, an attribute score and an ordering score, are computed as described in the following. The total score of a composite e-service is the summation of its attribute and ordering scores. Finally, the top N composite e-services are recommended to users according to the total scores.

The system computes the ordering score of composite e-services that include selected e-services. The ordering score of a composite e-service CS can be derived by the summation of $Sup(\langle x, y\rangle)$, for every $\langle x, y\rangle$ holds in the flow schema of CS. $Sup(\langle x, y\rangle)$ is derived from the mining result of frequent ordering sets.

The system gives each composite e-service an attribute score. The attribute score is computed for each flow schema of composite e-service that includes the selected e-services. The attribute score of a composite e-service CS is the summation of the attribute scores of its e-services. The attribute score of an e-service e is the summation of $Sup(p)$, for every attribute p in e. $Sup(p)$ is derived from the mining result of frequent attribute sets.

The total scores are derived by summing up the attribute scores and ordering scores. Notably, a weighted score can also be computed by multiplying the scores with corresponding weights. That is, Total Score $= (w_{\mathrm{p}} \times \text{Predicate Score}) + (w_{\mathrm{o}} \times \text{Ordering Score})$, where w_{p} and w_{o} are the weights of attribute and ordering score, respectively. The system ranks extracted composite e-service based on the total score, and recommends the top-N composite e-services to the users.

5.3.3. Group-based recommendations

The recommendation can be conducted by considering interest-groups to provide group-based recommendations. Customers with similar preferences are grouped into interest-groups as described in Section 5.1. For a customer u, the group-based recommendation proceeds as follows. The instance execution logs of u's interest-group are used to discover the frequent attribute sets of e-services and frequent ordering sets between e-services. Such discovered frequent attribute and ordering sets are then used to derive the scores of composite e-services and make recommendations.

5.3.4. E-service provider recommendations

Once a user decides upon a composite e-service and proceeds to use the e-services, he/her needs to choose an e-service provider for each e-service. The collaborative filtering (CF) approach is used to recommend e-service providers for the selected e-services. The CF approach finds the k-nearest neighbors (most similar users) of u, and then makes recommendations via considering the k-nearest neighbors' preferences on e-service providers and their similarity to u.

Through the user's k-nearest neighbors, the system can predict user's preference on an e-service served by a particular provider. The formula used to calculate the users' prediction score on an item j is shown in Eq. (2) (Resnick, Iacovou, Suchak, Bergstrom, and Riedl, 1994).

$$p_{u,j} = \overline{r_u} + \frac{\sum_{i=1}^{k} w(u,i)(r_{i,j} - \overline{r_i})}{\sum_{i=1}^{k} |w(u,i)|} \tag{2}$$

where $P_{u,j}$ is the prediction for the target user u on item j (an e-service served by a specific provider); $\overline{r_u}, \overline{r_i}$ is the average rating of user u (i); $w(u,i)$ is the similarity between active user u and user i; $r_{i,j}$ is the rating of user i on item j; and k is the number of user in the neighborhood.

6. System implementation and demonstration

6.1. System implementation

A prototype system is developed to demonstrate the effectiveness of the proposed Kmap platform. The implementation is conducted using several software tools, including ASP .NET(C#), JSP, Microsoft Visual Studio .NET and Borland J-Builder. The Web server is setup on Microsoft IIS 6.0 and Apache Tomcat 5. The Microsoft SQL server 2000 is used as the database system for storing related data of e-services and composite e-services. The Microsoft UDDI service is used as the UDDI engine for e-service search and registrations. Moreover, the data mining tool – Weka 3.4 is employed to discover the knowledge patterns as well as frequent attribute and ordering sets of composite e-services.

The XTM files for storing the discovered knowledge patterns including topics and associations in each cluster are generated according to the XTM defined in Sections 4.2 and 4.4. The XTM is adopted to develop the proposed knowledge map, providing a bridge for managing and exchanging heterogeneous resources of composite e-services. ASP.NET is employed to develop the Web-based navigator which allows users to browse and navigate the XTM information of composite e-services. Meanwhile, the recommendations of composite e-services are implemented via using the data mining and collaborative filtering techniques. The Kmap system is integrated with the recommendation capability to provide more effective knowledge support for managing and browsing composite e-services.

6.2. System demonstration

Fig. 6 shows the interface of the Kmap navigator. The left circle of Fig. 6 shows the clusters of composite

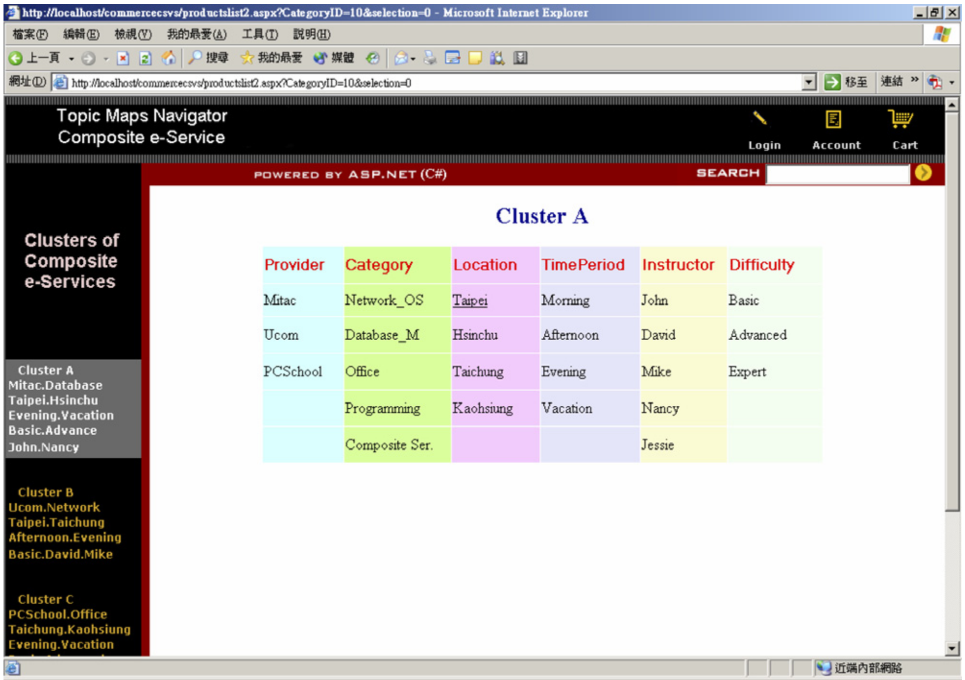


Fig. 6. Kmap navigator.

e-services with attributes of cluster centroid attached. Once a user selects a cluster to browse, the attribute values of the selected cluster (e.g. cluster A) can be browsed further in the navigator. Fig. 7 shows an example of browsing the topics in the navigator through Cluster A and then Location "Taipei". The "RelateTo" information lists the e-services that are associated to location "Taipei". The relevant information shows that the topics Instructor "Nancy" and Provider "Mitac" are relevant to the location "Taipei". Once a user selects an e-service "Programming a MS SQL Server 2000 Database", the Kmap system displays the detailed information, as shown in Fig. 8. The relevant e-services are also suggested to provide further navigations of relevant e-services.

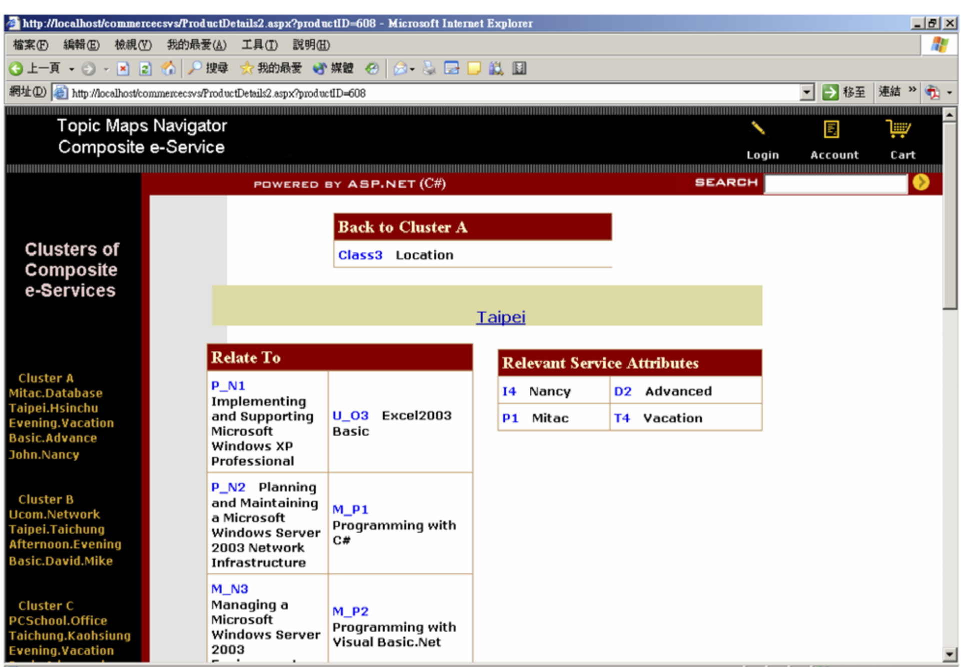


Fig. 7. A topic node "Taipei" with relevant service attributes.

When a user Mike logs in, the system identifies Mikes interest-group. Mike browses the cluster A of composite e-services to decide needed services. Fig. 9 shows the recommended composite e-services which are derived from the usage records of composite e-services conducted by Mike's interest group. Mike can click on any e-service in the selected composite e-service to obtain the details (frequent attribute values) of the clicked e-service, as

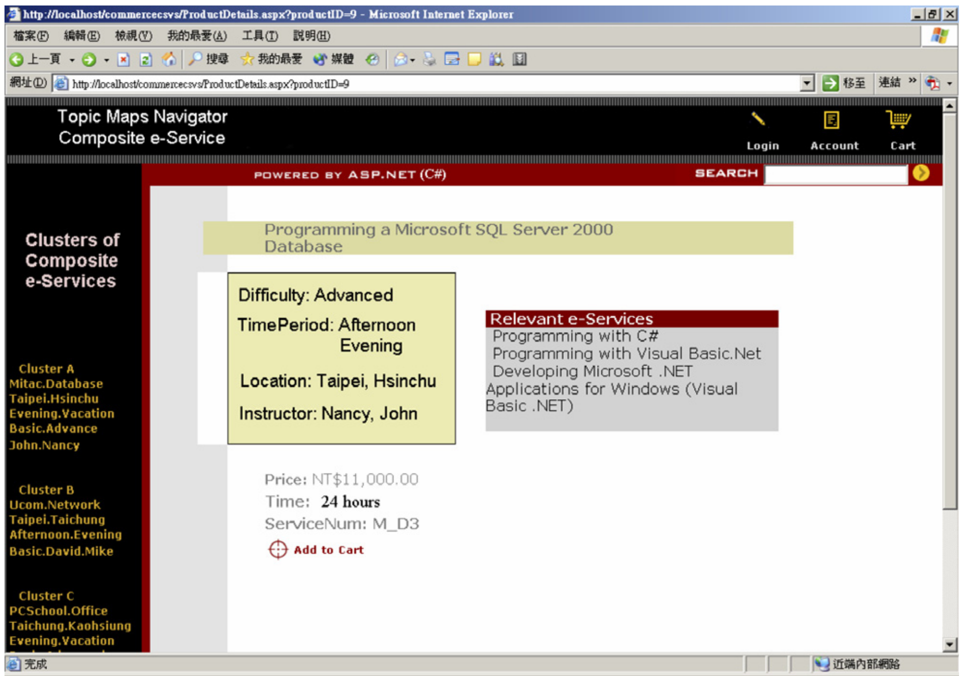


Fig. 8. A topic node "e-service" with relevant e-services.

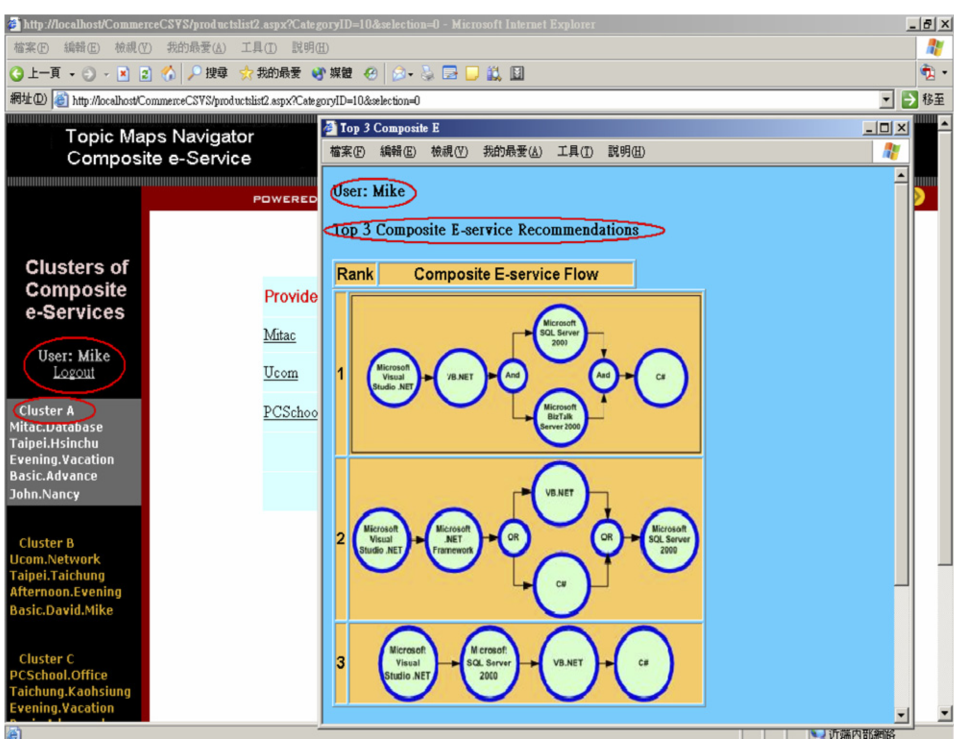


Fig. 9. Recommendations of composite e-services.

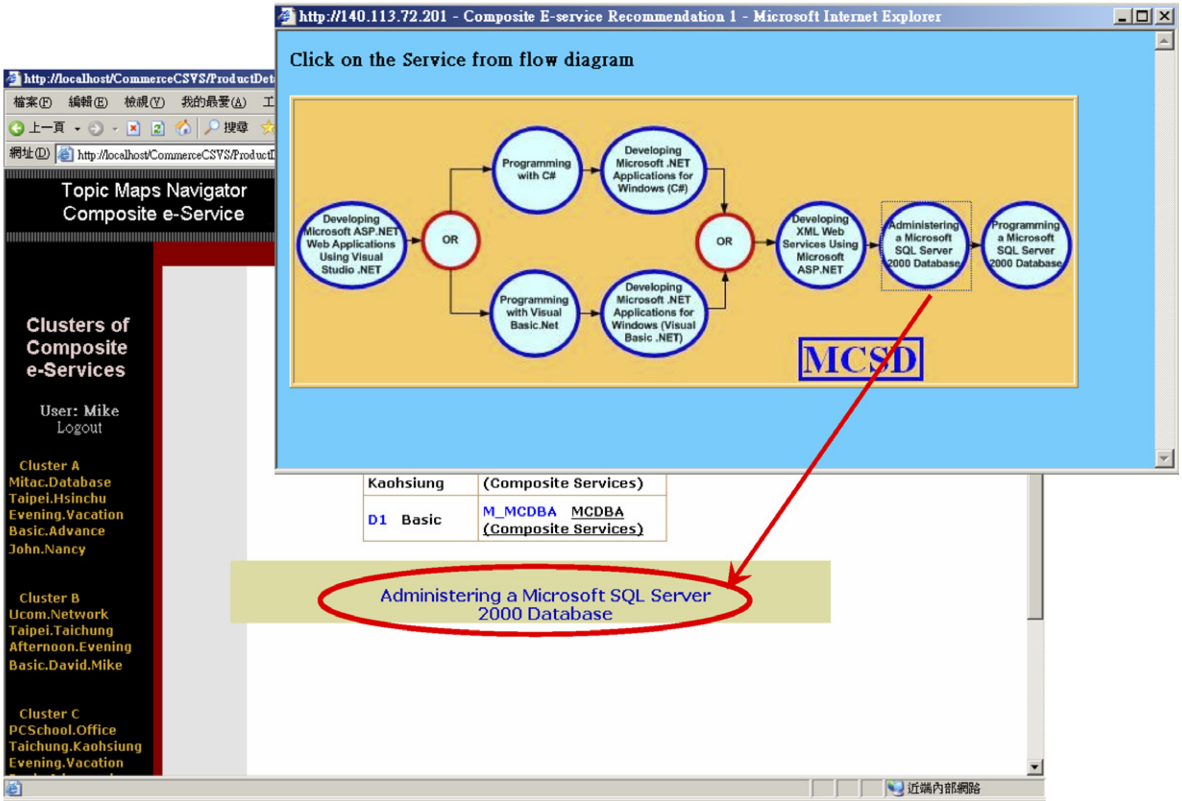


Fig. 10. Navigate an e-service in the recommended composite e-service.

shown in Fig. 10. The system can also suggest providers to serve the e-service via the collaborative filtering approach described in Section 5.3.4.

7. Conclusion and future work

This work mainly develops a Kmap system to provide knowledge supports for browsing and managing composite e-services. A system framework is proposed to deploy the knowledge maps of composite e-services. Data mining techniques are employed to discover valuable knowledge patterns of composite e-services. The discovered important subjects and association patterns are used as the kernel to generate the knowledge map. This work employs the XML topic maps to construct the knowledge maps of composite e-services. The XTM provides clear-cut hierarchical configurations of knowledge maps. Consequently, the knowledge maps of composite e-services, expressed in XML Topic Maps, can be exchanged and interoperated more easily on the Internet. Effective collaborations of conducting composite e-services over the Internet can thus be facilitated.

Moreover, the proposed system provides integrated browsing and recommendations of composite e-services. The relevant e-services or service attributes are recommended to users for decision support, while users use the Kmap navigator to search and browse composite e-services. The system also employs data mining and collaborative filtering to provide group-based recommendations of composite e-services. The proposed knowledge map enhanced with recommendations can provide user customized decision support to effectively utilize composite e-services.

This work contributes to proposing a system framework of providing knowledge supports for composite e-services. The prototype system is implemented using the simulation data set generated from the domain of training courses. Future work will be to evaluate the effectiveness of our proposed work on other application domains.

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XLANG, Web Services for Business Process Design, http://www.gotdotnet.com/team/xml_wsspecs/xlang-c/.

XML, Extensible Markup Language, World Wide Web Consortium (W3C) At URL: http://www.w3.org/XML.