A WEB-BASED LEARNING SUPPORT SYSTEM FOR ROUGH SETS

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Ying Zhou, candidate for the degree of Master of Science in Computer Science, has presented a thesis titled, ***A Web-Based Learning Support System for Rough Sets***, in an oral examination held on August 18, 2014. The following committee members have found the thesis acceptable in form and content, and that the candidate demonstrated satisfactory knowledge of the subject material.

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Abstract

Web-based learning is gaining popularity due to its convenience, ubiquity, personalization, and adaptation features compared with traditional learning environments. The learning subjects of Web-based learning systems are mostly for popular sciences. Little attention has been paid for learning cutting edge subjects and no such systems have been developed for rough sets.

Rough set theory has obtained significant attention as a mathematical approach to data representation and analysis in recent years. To realize Web-based learning for this subject, Web-based learning support systems can provide a reasonable framework. Web-based learning support systems sustain teaching as well as learning by making use of the Web technology, and are able to offer student-centered education.

This thesis presents the design principle, system architectures, and prototype implementation of a Web-based learning support system named *Online Rough Sets* (ORS). The system is specifically designed for learning rough sets in a student-centered learning environment. Some special features, such as adaptation, are emphasized in the system. The ORS has the ability of adaptation to student preference and performance by modifying the size and order of learning materials delivered to each individual. Additionally, it predicts estimated learning time of each topic, which is helpful for students to schedule their learning paces. Two demonstrative examples show ORS can support students to learn rough sets rationally and efficiently.

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Dedication

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Chapter 1

Introduction

The Internet has arisen as a main, and perhaps finally the major global communication channel for information and services [12]. It has boosted advances in computer technologies, especially the World Wide Web technology (the Web). The Web offers a distributed infrastructure for information processing and user-friendly interfaces without geographic restrictions [62]. Its wide application and advantages lead to the result that the educational paradigm has been transformed from the teacher-centered model to the student-centered model [16].

Web-based learning is obtaining popularity and provides many benefits compared with traditional learning environments [15, 71]. It is learning via electronic media on the Web [7]. Web-based learning is an alternative name of e-learning when the delivery channel (i.e., the Web) is emphasized [52]. Its learning content may consist of various forms of multimedia such as text, graphics, audio, video, and animation [46]. Web-based learning extends opportunities for education [27].

In post-secondary education, there are some Web-based learning systems for computer science subjects, such as, artificial intelligence, network security, information

retrieval, theory of computation, robotic, and system analysis [8, 21, 22, 26, 33, 34, 48, 49]. However, there are no Web-based learning systems for rough sets in the literature.

Rough set theory has gained significant attention as an intelligent tool dealing with uncertainty [3]. It is a mathematical approach to represent and reason uncertain data [72]. The fundamental idea of rough sets is the lower and upper approximations of a set [63]. Based on the approximations, the universe is divided into three regions, namely, the positive, boundary, and negative regions. A major advantage of rough sets is that rules extracted from the three regions can lead to application of the notion of three-way decision [67]. Rough set theory is also quite helpful when trying to find out important features and minimization of conditional attributes [59].

The aim of this dissertation is to design and prototype an effective Web-based learning system for rough sets. Web-based learning support systems (WLSS) provide a reasonable framework to realize Web-based learning. The WLSS sustain teaching as well as learning by making use of the Web technology, and offer learning environments which can be accessed by learners regardless of their time and places [61]. Learners are able to take courses in a Web-based learning support system which contains topics of subjects. Currently, there are some available WLSS to help educators and their learners in education [20, 29]. Moreover, well-designed WLSS can supply student-centered education [30].

A student-centered learning approach for adults, andragogy, may be suitable for rough sets learners, as most of them are adults. Andragogy aims to help adult learners according to the nature and characteristics of adults [43]. This approach is driven more by needs, experience, preference, and performance of students rather than those

of teachers.

In this thesis, we present a Web-based learning support system named Online Rough Sets (ORS). We combine WLSS with andragogy to support education, identify a set of rough sets concepts including their dependency information as structured learning materials, and collect a set of concept-specific quizzes. The design of ORS mainly depends on a learning model which is the realization of the learning process of andragogy. The learning model has the mechanism to generate adapted learning materials for each student. With this model, learning materials are tailored and sorted according to each student's preference. Learning materials delivered to a student will be automatically adjusted for review purpose when the student achieves poor performance on any quiz towards a learning material. Moreover, the ORS helps students schedule learning paces and improve learning efficiency by providing estimated learning time for each concept. The estimated learning time can help students reduce interruption caused by time shortage in learning a concept.

The thesis is organized as follows: Chapter 2 elaborates some background about Web-based learning systems in computer science subjects, rough sets, WLSS, technologies supporting WLSS, and andragogy; Chapter 3 describes the development of ORS including learning materials for rough sets, requirement analysis, system design, and implementation. The requirement analysis offers a proposed learning model, user groups, and representation of the model; Chapter 4 presents two demonstrative examples about how to learn rough sets using ORS as well as a comparison between ORS and existing systems; and Chapter 5 gives concluding remarks, summary of contributions, and future research.

Chapter 2

Background

This chapter offers some background and technologies to which this thesis relates. Firstly, we present related works in Web-based learning systems. Secondly, the notion of rough sets is introduced. Subsequently, we give the concept of Web-based learning support systems and its supporting technologies. Finally, a student-centered learning style for adults is introduced.

2.1 Web-based Learning Systems for Computer Science

Subjects

In this section, we firstly introduce Web-based learning. Subsequently, some Web-based learning systems for computer science subjects are reviewed, and their limitations are highlighted. These systems aim to apply Web-based learning in higher education especially at the graduate level. Typical subjects include theory of computation, artificial intelligence, robotic, network security, system analysis, and information retrieval.

2.1.1 Web-based Learning

Web-based learning is synonymous with e-learning in some situations.

E-learning refers to the use of electronic media with information and communication technology in education [52]. It is learning through electronic means [36]. The content of e-learning may consist of various forms of multimedia such as text, graphics, audio, video, and animation [46].

E-learning is broadly synonymous with Web-based learning, Web-based training, multimedia learning, computer-based instruction, computer-based training, computer-aided instruction, internet-based training, online education, online learning, virtual learning environments, and m-learning [38]. Each of these alternative names emphasizes a particular aspect, component or delivery channel [52].

Web-based learning is used to represent e-learning when the delivery channel (i.e., the Web) is emphasized [7, 50]. It eliminates the barriers of time and geographical distance in education [27]. Students can participate in their online courses when the Internet is available regardless of their physical locations [27]. Web-based learning also allows students to take courses in a cost effective platform [15]. It offers a second chance to many people for educating themselves [8].

As shown in Table 2.1, Web-based learning can be applied to different sectors and phases in education. These areas include k–12, higher education, and corporate.

Table 2.1: Application scope of Web-based learning

Scope	Description
K–12	Kindergarten, elementary, junior high, and senior high [44]
Higher education	Post-secondary including undergraduate and graduate [54]
Corporate	Career training for employees or customers of companies [45]

2.1.2 Review of Web-based Learning Systems for Computer Science Subjects

There are some Web-based learning systems for computer science subjects reported in the literature. Seven systems are reviewed in this section. Each of these systems aims to support the learning of one subject, with a total of six subjects in computer science involved. We discuss each system in detail and highlight its advantages and disadvantages. The subjects discussed are introduced in the order of theory of computation, artificial intelligence, robotic, network security, system analysis, and information retrieval.

For theory of computation, a weak ontology is used to organize learning materials in an undergraduate program [34]. Concepts related to automata and formal languages have been organized into a hierarchy. The advantage is that the ontology may be used to personalize learning materials based on inference rules and learners' input. The disadvantage is that the ontology only contains the is-a relation among concepts in the hierarchy. In other words, a concept must have and only have one parent concept. Moreover, architectures and implementation of the system are not mentioned.

In another system for theory of computation, a robot is utilized to simulate the details of finite state automata [21]. The system consists of a finite state automaton simulator and a robot. Learners are required to build their own automata graphically in the simulator interface and pass them to the robot. The robot can simulate the automaton transitions. Learners study by observing motions of the robot and playing an off-system game. In the game, a group of learners guess their mutual

input to strengthen their understanding after observing motions of the robot. The advantage is that details of each automaton are remotely displayed by a real robot. The disadvantage is that the simulator only covers one specific topic of the course, and the game is not a part of the system.

For artificial intelligence, an interface is developed to manipulate input and output of prolog-programmed scripts through the Web [33]. The interface is a web page which offers input options, interprets the options, validates input, and prepares the input to students' prolog predicates. On the output side, the interface explains and formats the output from students' scripts. The advantage is that learners can run their scripts through the Web without installing compile environments on their own computers. The disadvantage is that it doesn't support any other functions.

For robotic, a simulator connecting with a real robot is built to perform experiments [26]. The system aims to ease the difficulty for students to perform actual experiments due to the lack of real robots. The system consists of multimedia contents, a 3D robot simulator, and a real robot. The 16 weeks contents comprises moving pictures, animation, and synthesized voice. The advantage is that a learner can remotely experiment with both a virtual robot and a real one. The disadvantage is that learning materials are fixed and no assessment is mentioned.

For cryptography in network security, the system generates adapted learning materials after a student querying on a particular concept [49]. It contains a set of concepts in cryptography domain and their dependent relationships as an ontology. Each student is required to choose a concept and depth of dependency before querying. The system generates a sequence of concepts after a student querying. The sequence adapts to difficulty based on the learning history of that student, and guides the

student to learn concepts in this sequence. Related assessment is conducted after learning. The advantage is that learning materials can adapt to student preference and learning history. The disadvantage is that a student can't query on multiple concepts per time, and sequences can't adapt to performance.

For system analysis, a 3D role-play game supports students to learn the waterfall development model by themselves [8, 48]. The system is a game-based self-learning environment used to assist teaching in an undergraduate course. It also assesses student motivation, satisfaction and learning achievements. The game story is set in a practical office environment, and includes several scenes corresponding to different roles. In each scene, learners study the knowledge in a specific role by viewing goals, executing tasks, and accepting assessment. The advantage is that the game of the system is attractive. The disadvantage is that adaptation to assessment is not considered.

For fuzzy information retrieval systems, a simulator is developed to visualize the steps of weighted queries in a graduate course [22]. It aims to solve the problem that a blackboard is very difficult to visualize the content of weighted queries and fuzzy connectives. The system offers students the opportunity to see and compare the results of different weighted queries. It provides visualization tools to better show evaluation processes of queries step by step. The advantage is that each step can be reviewed clearly. The disadvantage is that the system is just an educational tool for better presentation.

2.1.3 Limitations

Although these learning systems have various advantages, there are still some limitations. We list a few common ones in the following: (1) no adaptation to performance is made; (2) no systems offer queries on multiple concepts; (3) learning materials of systems are organized in a fixed manner except the system for cryptography in network security; and (4) some systems are only simulators or interfaces for the purpose of displaying steps clearly.

2.2 Rough Sets

Rough set theory was proposed by Pawlak in 1980s [72]. This section firstly presents two important models of rough sets, namely, the standard rough set model and the probabilistic rough set model. Subsequently, some applications based on rough sets are introduced.

2.2.1 Standard Rough Set Model

For the lower and upper approximations, their definitions rely on two extreme cases considering the relationships between a set and a series of equivalence classes [66]. Suppose U is a non-empty finite set of objects, called the universe U . Let E be an equivalence (indiscernibility) relation on U , i.e., $E \subseteq U \times U$ is reflexive, symmetric, and transitive. The equivalence class of E containing an object $x \in U$ is denoted as $[x]_E = [x] = \{y \in U | xEy\}$. The family of equivalence classes defined by E is $U/E = \{[x]_E | x \in U\}$, and is also called a partition induced by E .

Suppose C is a subset of U , called a concept. The lower and upper approximations

of C are defined as below:

$$\begin{aligned}\underline{apr}(C) &= \{x \in U \mid [x]_E \subseteq C\}, \\ \overline{apr}(C) &= \{x \in U \mid [x]_E \cap C \neq \emptyset\}.\end{aligned}\tag{2.1}$$

The three regions are defined as below:

$$\begin{aligned}\text{POS}(C) &= \underline{apr}(C), \\ \text{NEG}(C) &= U - \overline{apr}(C), \\ \text{BND}(C) &= \overline{apr}(C) - \underline{apr}(C).\end{aligned}\tag{2.2}$$

The positive region $\text{POS}(C)$ contains those equivalence classes which definitely belong to C . In contrast, the negative region $\text{NEG}(C)$ contains those equivalence classes which definitely don't belong to C . For each equivalent class in the boundary region $\text{BND}(C)$, one part of its objects belong to C , while another part not.

The division of three regions using the standard rough set model is too strict [68]. The degree of overlap between an equivalence class and a concept is not considered. The boundary region is relatively large, while the positive and negative regions are relatively small [68]. This causes unnecessary limitations in application, and many researchers investigate the probabilistic rough set model to ease such limitations [66].

2.2.2 Probabilistic Rough Set Model

The probabilistic rough set model utilizes a pair of thresholds (α, β) to divide the three regions [66]. The probabilistic association between an equivalence class and

a concept C is compared with the thresholds to determine the three regions. The probabilistic association is the basis of the model [42] and is shown as follows:

$$Pr(C|[x]) = \frac{|C \cap [x]|}{|[x]|}, \quad (2.3)$$

where $|\cdot|$ denotes the cardinality of the inside set, $[x]$ is the equivalence class, and C is a subset of the universe. The probabilistic association $Pr(C|[x])$ implies the conditional probability of an object $x \in C$, given that the object $x \in [x]$.

The lower and upper approximations of C divided by the pair are:

$$\begin{aligned} \underline{apr}_{(\alpha,\beta)}(C) &= \{x \in U | Pr(C|[x]) \geq \alpha\}, \\ \overline{apr}_{(\alpha,\beta)}(C) &= \{x \in U | Pr(C|[x]) > \beta\}. \end{aligned} \quad (2.4)$$

The three regions are defined as below:

$$\begin{aligned} \text{POS}_{(\alpha,\beta)}(C) &= \{x \in U | Pr(C|[x]) \geq \alpha\}, \\ \text{BND}_{(\alpha,\beta)}(C) &= \{x \in U | \beta < Pr(C|[x]) < \alpha\}, \\ \text{NEG}_{(\alpha,\beta)}(C) &= \{x \in U | Pr(C|[x]) \leq \beta\}. \end{aligned} \quad (2.5)$$

The three regions can be more practical compared with those based on the standard rough set model. The degree of overlap between an equivalence class and a concept is considered. By adjusting the thresholds, the model allows the boundary region to become smaller, while the positive and negative regions may become larger. Larger positive and negative regions are helpful to make decision [70].

Based on the probabilistic rough set model, recent development of rough sets includes some models, such as the decision-theoretic rough set model [65, 67], the game-theoretic rough set model [60], and the information-theoretic rough set model [11]. These models differ in how to calculate the pair of thresholds. With such variety, rough sets may be applied in more areas.

2.2.3 Applications of Rough Sets

In the field of decision making, the decision-theoretic rough set model is utilized to make three-way decision especially when a nondeterministic situation is meaningful and practical [69]. The game-theoretic rough set model is incorporated to a Web-based medical decision support system in order to perfect the three-way decision making [58].

In the field of data mining, the game-theoretic rough set model is used to conduct feature selection and attribute classification [1, 2]. Support vector technologies are extended by rough sets for classification, prediction, and clustering [35].

In the field of education, a system can predict student performance by reduct and rule induction based on the standard rough set model [14].

2.3 Web-based Learning Support Systems

This section presents the basic idea, functions, and an architecture of Web-based learning support systems.

2.3.1 What are WLSS

Web-based learning support systems is a specific category of Web-based support systems [15]. Web-based support systems (WSS) refers to a new multidisciplinary research area which studies the Web as the interface, repository and resource center to support human activities [57].

Learning is a dynamic and interactive feedback process in exploring an external environment, and this process is always accompanied with active and imagination driven actions [41]. There are two main learning styles: teacher-centered learning and student-centered learning [15]. Teacher-centered learning is always used in a traditional classroom. Teachers and students communicate bidirectionally in real time. In the student-centered education, students choose what and how they will learn individually, and their abilities, needs, and learning styles are focused [40]. Students are required to be active and responsible participants in their own learning, while teachers or instructors play as supporters or facilitators of learning [15]. This learning style benefits students with personal flexibility.

The WLSS are combination of WSS and learning. The WLSS support teaching and learning by using the Web as an interface, repository, and resource center [30]. Well-designed WLSS are able to offer a student-centered form of education [30].

2.3.2 Functions of WLSS

Fan suggests a Web-based learning support system should consider four major functions, namely, the complexity of learning support, the adaptability support, the interaction support, and the assessment support [14]. This conversely means that a

system can be categorized into WLSS if it can offer those functions through the Web.

The complexity of learning support considers how many actions in the learning process can be supported. The learning process should involve multiple actions. For example, many humans like to interact and collaborate. Experience and obtained knowledge are used in the new cognition. Examples help students consolidate and strengthen their skills. Without these activities, the knowledge presented is always fixed and hard to learn.

The adaptability support means that the system can adapt to each student by considering his/her ability and skill level. The learning materials of instruction, the sequence of topics, the difficulty of topics, and other parameters of instruction are adaptive to each student's experience and performance.

The interaction support enables students to communicate with the system bidirectionally. Learners should be able to store customized annotations and notes to the learning materials. It should allow learners to ask questions and retrieving correct answers in a short period.

The assessment support offers interfaces to evaluate student performance. Testing occupies an important role in evaluating and assessing student progress as well as the check point analysis. Exercises are used to enhance student understanding of each topic through practice. The system should offer each student the opportunity to practice and get according feedback.

2.3.3 An Architecture of WLSS

Since WLSS is a specific category of WSS, the general architecture of WLSS inherits some features of WSS, such as the multi-layer design and Web-based user

Figure 2.1: An architecture of Web-based learning support systems

interfaces. Architectures of WLSS may vary depending on functions they emphasize, such as the assessment support.

Figure 2.1 shows a demonstrative architecture of WLSS [30]. Based on a treasure hunt game, the system implements the idea of inquiry-based learning to boost student motivation for the purpose of improving effectiveness. The teaching support subsystem enables instructors to design different inquiry-based learning environments according to students. The learning support subsystem sustains inquiry activities of students. The treasure hunt game allows students to study new knowledge, develop thoughts, and review their achievements [30].

2.4 Technologies Supporting WLSS

In this section, we present the basic notions of some import technologies used in developing Online Rough Sets.

2.4.1 Constraint Satisfaction Problem for Formulating ORS

In this thesis, we use a constraint satisfaction problem (CSP) to represent the problem of how to generate a personalized learning sequence for a learner. Lots of problems in computer science and artificial intelligence can be treated as special cases of the CSP, such as scheduling, graph problems, circuit design, and temporal reasoning [47]. We treat the generation of a learning sequence as a scheduling problem, and use a CSP to represent and solve it.

In artificial intelligence, a CSP is defined by a set of variables $\{x_1, x_2, \dots, x_n\}$ and a set of constraints $\{c_1, c_2, \dots, c_m\}$ [47]. Each variable x_i has a nonempty domain D_i of possible values. Each constraint c_i involves a subset of variables and specifies the allowable combinations of values for this subset. There are two types of constraints, namely, hard constraints and soft constraints.

Hard constraints are physical characters which have to be necessarily satisfied, such as spatial and temporal constraints. Soft constraints are properties which should be satisfied as best they can after the hard constraints being met, such as due dates, user preference, and cost [17]. Soft constraints are simply ignored sometimes.

The solution is an assignment of values to some or all of the variables such as $\{x_i = v_i, x_j = v_j, \dots\}$. Various searching methods can be used to find a solution, such as the depth-first search.

2.4.2 Cluster Analysis for Grouping Learners

In this thesis, cluster analysis supports to calculate the estimated time. Cluster analysis (or called clustering) is the job of categorizing a set of objects. Objects

inside a same group (named a cluster) are more alike with each other, than with those in other groups (clusters excluding the previous cluster). Among the clusters found by different algorithms, objects vary obviously on their inherent characters. In exploratory data mining, cluster analysis is considered as a major job [13].

Various algorithms can be used to conduct cluster analysis. They differ apparently in the concept of what consists a cluster and how to locate them with high efficiency [56]. Some typical algorithms include K-Means, Expectation-Maximization, DBSCAN, and hierarchical clustering [53].

2.4.3 Moving Average Analysis for Time Series Data

In this thesis, a moving average supports to calculate the estimated time of each concept. In statistics, a moving average is a type of filter offering finite impulse response. It creates a series of averages from different subsets of the data set. These averages are used to analyze a set of data points [18]. It is also called a running average, rolling average, rolling mean, moving mean, or sliding temporal average.

A moving average is commonly applied on time series data in order to smooth out fluctuations in short terms and highlight trends in long terms [18]. The thresholds of short-term and long-term depend on the situation. The parameters of the moving average will be set accordingly. Some typical types of the moving average include simple moving average, cumulative moving average, weighted moving average, and exponential moving average [24, 28].

2.5 A Student-centered Learning Style for Adults

Andragogy is a term to represent the art and science of how to teach adults [37]. In order to introduce andragogy, pedagogy is presented firstly.

Pedagogy: Teacher-centered Style

Pedagogy literally implies leading children [37]. It is also called a traditional or teacher-centered learning approach. In Europe and America, pedagogy remains as the main format for instruction [23]. It is based on the assumption that learners only need to know what the instructors teach them, and places students in a submissive role [23]. In this case, the teaching and learning mainly depends on instructors.

Andragogy: Student-centered Style

Andragogy is the opposite to pedagogy, and aims to help adults learn better [32]. It is also called a non-traditional or student-centered learning style. Andragogy is based on six assumptions: (1) adults need to know the reason of learning; (2) experience provides the basis; (3) adults need to participate the planning; (4) the learning is problem-centered; (5) the learning should have immediate relevance to adults; and (6) adults respond better to internal motivator [5, 9].

The learning process of andragogy involves eight steps: (1) preparing learners; (2) establishing a climate; (3) involving learners in mutual planning; (4) diagnosing learning needs; (5) forming learning objectives; (6) designing plans with learners; (7) carrying out plans; and (8) evaluating outcomes [25]. Andragogy is capable to be integrated in WLSS which has flexibility to enable a student-centered learning style.

Chapter 3

Online Rough Sets Development

This chapter describes the proposed system in different aspects including content of the system, requirement analysis, system design, and implementation.

3.1 Learning Materials for Rough Sets

Complex knowledge can be separated into a network of prerequisites [10]. Learners should master relevant prerequisites before moving to another higher level knowledge [10]. As the knowledge of rough sets can be represented by a series of formulas, it is possible to decompose them into a set of concepts with dependency. With notes, assignments, and exams of the “Rough Sets & Applications” course offered at the University of Regina, it is possible to identify the knowledge as a set of concepts, dependency, and concept-specific quizzes.

3.1.1 Concepts of Rough Sets

Hierarchical organizations and structures of complex knowledge can be generated by a strategy named the divide and conquer [64]. Table 3.1 shows the 68 concepts that

we have identified with the strategy in five groups, namely, the *Basic*, the *General*, the *Advanced*, the *Application*, and the *Others*.

The group of *Basic* contains 24 concepts of rough sets. They are the most basic concepts in the subject. Students need to master those concepts if they want to study more advanced concepts. Typical concepts include *Information table*, *Definable set*, *Partition of universe*, *Equivalence class (EC)*, *Three regions of rough sets*, and *Discernibility matrix (DM)*.

The group of *General* contains 18 concepts of the subject. They depend on concepts of the *Basic* group, and are the prerequisites for understanding the *Advanced* group. Typical concepts include *Degree of overlap*, *Interpretation of (α, β)* , *Attribute reduct*, *Core-attribute*, *Reduct-attribute*, *Deletion-based reduct*, and *Matrix absorption*.

The group of *Advanced* contains 12 concepts of the subject. They are some complex concepts based on the groups of *Basic* and *General*. Students may need to spend over one hour to master one concept of this group. Typical concepts include *PRS*, *DTRS*, *Relative attribute reduct*, and *Reduct using DM*. The number of concepts in this group may increase significantly in the future.

The group of *Application* contains 2 concepts, namely, *Bayesian theorem on PRS* and *Bayesian decision procedure on PRS*. The two concepts are dependent ones for understanding the *Advanced* group. They involve how to apply theorems of other subjects on rough sets concepts. For instance, *Bayesian decision procedure on PRS* is the result of applying *Bayesian decision procedure* on the concept of *PRS*.

The group of *Others* contains 14 concepts of other subjects. They are dependent concepts for mastering the *Basic* and *Application* groups. Typical concepts include *Logic connective*, *Set operator*, *Power set*, *De Morgan's laws*, *Binary relation (BR)*,

Table 3.1: Concepts of rough sets

Group	Concept	Group	Concept
Basic	Information table	General	Deletion-based reduct
	Equivalence relation (ER)		Advantage of relative reduct
	Concept in an information table		Matrix absorption
	Definable set		Addition-deletion-based reduct
	Family of definable set		Addition-based reduct
	Partition induced by ER		Powerset-based reduct
	Family of undefinable set	Advanced	PRS
	Property of definable set		DTRS
	Family of concept		GTRS
	Partition of universe		Development of PRS
	Property of ER		Equivalence relation rule
	Approximation on definable set		Element-based rough sets
	Property of definable set 2		Granule-based rough sets
	Decision table		Subsystem-based rough sets
	Discernibility matrix (DM)		Relative attribute reduct
	Non-equivalence relation		Reduct
	Semantic Meaning of ER		Duality
	Equivalence class (EC)		Reduct using DM
	Description of EC	Application	Bayesian theorem on PRS
	Element of DM		Bayesian decision procedure on PRS
	Property of approximation	Others	Concept
	Three regions of rough sets		Logic connective
General	Simplification		Means of formula
	Minimum DM		Logic language
	Boolean algebra		Power set
	Degree of overlap		Set operator
	ER based on BR		De Morgan's laws
	Description 2 of EC		Lattice
	Interpretation of (α, β)		Binary relation (BR)
	Attribute reduct		One-to-one correspondence
	Non-reduct-attribute		Bayesian theorem
	Core-attribute		Probabilistic independence assumption
	Reduct-attribute		Bayesian decision procedure
	Monotonicity property		Nash equilibrium

Bayesian theorem, and Probabilistic independence assumption.

Besides, each concept has a description of its notion, a group of detailed formulas, and several examples.

3.1.2 Dependency among Concepts

Dependency exists among related concepts. There are 103 dependent relationships among the above 68 Concepts. Each relationship involves a parent concept and a child one. Understanding the parent concept is the prerequisite for learning the child one.

Table 3.2: Part of the dependency among concepts of rough sets

Prerequisite Concept	Concept
Set operator	Information table
Information table	Equivalence Relation
Information table	Logic language
Logic connective	Logic language
Information table	Means of formula
Logic language	Means of formula
Concept	Concept in an information table
Information table	Concept in an information table
Logic language	Concept in an information table
Means of formula	Concept in an information table
Information table	Definable set
Logic language	Definable set
Means of formula	Definable set
Definable set	Family of definable set
Power set	Family of definable set
Family of definable set	Approximation on definable set
Set operator	Approximation on definable set
Family of definable set	Property of definable set
Lattice	Power set
Equivalence relation	Partition induced by ER
Partition of universe	Partition induced by ER
Family of definable set	Family of undefinable set
Power set	Family of undefinable set

In other words, students should not study the child concept if they do not master the parent one. Those relationships make up a hierarchical structure among the concepts.

For illustration, Table 3.2 partly lists dependency among concepts of rough sets. In this table, the column of *Prerequisite Concept* corresponds to parent concepts, while the column of *Concept* represents child concepts. For instance, a student needs to master *Set operator* before studying *Information table*. *Definable set* has three prerequisite concepts including *Information table*, *Logic language*, and *Means of formula*. All the three concepts should be mastered by students before learning *Definable set*.

3.1.3 Quizzes of Concepts

Every concept is accompanied with its own quizzes. Mastering a concept means the student has to successfully pass all its quizzes. The types of quizzes include choice selection and fill-in-the-blank.

For a quiz of choice selection, it contains a question and several answers including both right and wrong solutions. For instance, a question of *Logic language* is “Please select a true one from the following statements, where the domain is all real numbers.” The four candidate answers are in Equation (3.1). In this case, the right solutions are (a) and (b), while the wrong solutions are (c) and (d).

$$\begin{aligned}
 (a) \quad & \exists_x(x^4 < x^2), \\
 (b) \quad & \exists_x(x^2 > x), \\
 (c) \quad & \forall_x((-x)^2 = x^2), \\
 (d) \quad & \forall_x((-x)^2 > x)\}.
 \end{aligned} \tag{3.1}$$

For a quiz of fill-in-the-blank, it contains a question together with an improper answer, and students need to complement this answer correctly after reading the question. For instance, a question of *Granule-based rough sets* is “Please complement the blanks in the formula which represents the granule-based rough sets, given E is an equivalence relation on U and $C \subseteq U$.” The improper answer is Equation (3.2), and the right solution is Equation (3.3).

$$\begin{aligned}\underline{apr}(C) &= \cup\{[x] \mid [x] \in U/E, [x] \text{ please fill } C\}, \\ \overline{apr}(C) &= \cup\{[x] \mid [x] \in U/E, [x] \text{ please fill } C \text{ please fill}\}.\end{aligned}\tag{3.2}$$

$$\begin{aligned}\underline{apr}(C) &= \cup\{[x] \mid [x] \in U/E, [x] \subseteq C\}, \\ \overline{apr}(C) &= \cup\{[x] \mid [x] \in U/E, [x] \cap C \neq \emptyset\}.\end{aligned}\tag{3.3}$$

3.2 Requirement Analysis

The aim of ORS is to support students to learn rough sets through the Web in a student-centered learning environment. The learning materials of ORS are a set of concepts with dependency presented in Section 3.1.1, and each concept is accompanied with a set of concept-specific quizzes.

3.2.1 A Learning Model of ORS

A learning model of ORS is the realization of the eight-step learning process which is described in Section 2.5. The learning model supports students to study

those dependent concepts from bottom to top with some personalization. It also ensures that prerequisites of a concept must be studied again when learners fail to pass the concept's quizzes [10]. This is done by adding a loop between *Forming learning objectives* and *Evaluating outcomes*. Figure 3.1 shows the learning model and its emphasis (i.e., preference, performance, and estimated time).

A *concept* is a unit of learning materials defined by experts, and is introduced in Section 3.1.1. An item of *dependency* is a dependent relationship between two concepts which is introduced in Section 3.1.2. A *range* defined by tutors points to several concepts, and is used to help students choose their learning objectives. A *goal* indicates several concepts selected by a student from either a concept list or ranges. An item of *experience* is a group of concepts which appear in a goal and have been

Figure 3.1: A learning model of ORS

mastered by the student. An item of *preference* contains prioritized constraints based on concept characters (e.g., the difficulty, the relevance, the sub-subject, the media type), and is used to customize learning sequences for everyone.

Learning materials delivered to each individual are organized in a *study plan*. The *study plan* contains a learning sequence and estimated time for learning each concept. The learning sequence guides a student to learn concepts one by one sequentially. The estimated time indicates how long a learner may need to learn each concept. It helps a student allocate proper time to learn a concept, and thus helps the student reduce interruption caused by time shortage in learning this concept. The estimated time can improve learning efficiency, since learners need more time to finish a task in case it has been interrupted [4].

Adaptation of Web-based learning systems focuses on curriculum sequencing to guide students and diagnose their misconceptions through their learning processes [6]. In the above learning model, adaptation to preference means that ORS forms a learning sequence based on dependency and learner preference. Adaptation to performance means that ORS modifies a learning sequence by adding prerequisites of a concept into this sequence when the student achieves poor performance on this concept.

An example is presented to introduce the running of the above learning model. Suppose a student has a *goal* containing 7 concepts, namely, *Set operator*, *Logic connective*, *Information table*, *Logic language*, *Means of formula*, *Concept*, and *Concept in an information table*. We also assume his *experience* contains the first 4 concepts as listed. His *gap* becomes *Means of formula*, *Concept*, and *Concept in an information table*. The difficulty levels of the difficulty character on the 3 concepts are *normal*, *low*, and *normal*, respectively.

After the student selecting and configuring the character of difficulty as preference (e.g., from high to low), a study plan is generated based on dependency and preference. It contains a learning sequence of *Concept* $\rightarrow$ *Means of formula* $\rightarrow$ *Concept in an information table*. The step of *Get next concept* results the start of learning *Concept*. According to the estimated time in the study plan, the student can evaluate whether or not he has enough time to learn this topic for the purpose of reducing interruption caused by time shortage.

Suppose the student decides to learn *Concept*, and passes its related quizzes. The *gap* becomes *Means of formula* and *Concept in an information table*. Subsequently, the student learns *Means of formula* but fails on its quizzes. The learning model modifies the *gap* by adding the prerequisite concepts of *Means of formula* based on dependency. The *gap* becomes *Logic language*, *Means of formula*, and *Concept in an information table*.

Based on the new *gap*, the *study plan* is updated. The student learns concepts according to the new *study plan*. In this process, the learning model may increase or decrease the size of *gap* due to the student's performance. The learning model will end the process after the *gap* becoming empty.

3.2.2 User Groups

There are four groups of users, namely, expert, tutor, student, and administrator. Experts are responsible for defining learning materials, dependency, and their characters. Tutors help students customize these learning materials. Students define their preference and study the personalized learning materials. Administrators manage the menu, roles, and other configuration of the system.

Figure 3.2: Relationships among users of ORS

Among the four groups of users, their relationships can be expressed in two typical scenarios as shown in Figure 3.2. For all scenarios, experts can define learning materials with support of administrators. Students can use the system with support of experts and administrators.

In scenario 1, a student enrolls a lecture course of rough sets. A tutor (instructor) defines several ranges according to different student expectations. The student is supposed to select an appropriate range according to his situation. For this student, the study on ORS is supplementary to the lecture. In scenario 2, a student learns individually. The student is supposed to choose a few concepts and study them by himself through ORS. A person who wants to learn the subject systematically by himself is also supposed to use ORS in this way.

3.2.3 Representing the Learning Model

This section describes the representation of the learning model presented in Section 3.2.1. Topics in this section include concept, knowledge, learning order relationship, partial order, preference, and learning sequence.

Concept and Knowledge

Concepts of rough sets are listed in Section 3.1.1. Each concept refers to its name, description, links of learning content, related quizzes, and values of characters. A concept C can be expressed by a tuple:

$$C = \{id, N, I, L, Q, P\}, \quad (3.4)$$

where id is a unique identifier of the concept;

N is a set of names of the concept;

I is a set of intensions which are description of the concept;

L is a set of hyper links which connect to the learning content;

Q is a set of pairs of (*question, answers*) which are used as quizzes;

P is a set of pairs of (*character, character_value*), such as (*difficulty, low*).

For each concept, it can relate to several characters, and has one and only one value on each character. The time spent on a concept consists of two parts, namely, understanding its intensions and solving its quizzes.

In computer science and information science, the knowledge of a subject (or domain) can be represented as a set of concepts and relationships between pairs of concepts from the perspective of ontology. If a student wants to learn a subject, the student needs to master its concepts and their relationships at least. In this thesis, we define the set of concepts of a subject as $SC = \{C | C \text{ is a concept}\}$.

Learning Order Relationship among Concepts

A learning order between two concepts $C1$ and $C2$, is called a *learning order relationship* if and only if learning $C1$ is a prerequisite for learning $C2$. It is denoted by:

$$C1 \preceq C2, \quad (3.5)$$

where $C1, C2 \in SC$, $C1$ is called a parent concept, and $C2$ is called a (child) concept.

The learning order relationship has same meaning with the dependent relationship introduced in Section 3.1.2. In terms of a subject SC , its learning order relationships construct a hierarchical structure among its concepts, and can be denoted by:

$$LOR_{full} = \{(x, y) | x \preceq y, x \neq y, x \in SC, y \in SC\}. \quad (3.6)$$

For instance, we assume a subject and its learning order relationships as follows:

$$SC = \{C1, C2, C3, C4, C5, C6, C7\},$$

$$LOR_{full} = \{(C3, C2), (C2, C4), (C1, C4), (C4, C6), (C5, C7)\}.$$

In terms of $C4$, there are $C1 \preceq C4$ and $C2 \preceq C4$. We can also say that learning $C1$ and $C2$ is necessary to learn $C4$.

The knowledge state means the state of learning. A knowledge state contains a set of concepts, and the prerequisites of these concepts are also included in the set. A subset $KS \subseteq SC$ is called a knowledge state on SC , if it satisfies:

$$\forall_{y \in KS} (\neg \exists_{x \in SC} ((x, y) \in LOR_{full}) \bigvee \forall_{(x, y) \in LOR_{full}} (x \in KS)), \quad (3.7)$$

where SC denotes the set of concepts of a subject;

LOR_{full} denotes learning order relationships of the subject.

For instance, $\{C2, C3, C5\}$ is a knowledge state in the above example. The subset contains all the prerequisites of its elements.

Not every subset of SC is a knowledge state. For instance, $\{C2, C5\}$ is not a knowledge state in the above example. The prerequisite of $C2$ is $C3$, but $C3$ doesn't belong to the subset.

The family of all possible knowledge states is called the knowledge structure (KST), denoted by:

$$KST = \{KS \subseteq SC \mid \forall_{y \in KS} (\neg \exists_{x \in SC} ((x, y) \in LOR_{full}) \bigvee \forall_{(x, y) \in LOR_{full}} (x \in KS))\}. \quad (3.8)$$

We can treat the objectives chosen by a student as an arbitrary subset $A \subseteq SC$. The subset A can be transformed to a knowledge state KS_A by:

$$\begin{aligned} BaseCase : KS_A &= A \cup \{x \in SC \mid x \notin A, y \in A, (x, y) \in LOR_{full}\}, \\ Recursive : KS_A &= KS_A \cup \{x \in SC \mid x \notin KS_A, y \in KS_A, (x, y) \in LOR_{full}\}. \end{aligned}$$

For instance, a subset $A = \{C2, C5\}$ is not a knowledge state in the above example. It can be transformed into the knowledge state $KS_A = \{C2, C3, C5\}$ by adding $C3$ into itself. The $C3$ is the result of searching prerequisites of A according to LOR_{full} .

Suppose subset $Obj \subseteq SC$ contains the objectives selected by a student. The *Goal* is KS_{Obj} . The student needs to learn all concepts in the *Goal* for the purpose of completing his/her objectives.

Before starting to learn the *Goal*, the student may have mastered some of its

concepts. These concepts are unnecessary to be studied again. The *Experience* represents those concepts, and $Experience \subseteq Goal$.

As the time as the *Experience* is marked by the student, a simpler set of learning order relationships $LOR \subseteq LOR_{full}$ can be denoted by:

$$LOR = \{(x, y) | (x, y) \in LOR_{full} \wedge y \in Goal \wedge x \notin KS_{Experience}\}. \quad (3.9)$$

The *Gap* is the real learning objectives after considering the student's *Goal* and *Experience*. It contains a set of concepts, and is denoted by:

$$Gap = Goal \cap \overline{KS_{Experience}}. \quad (3.10)$$

Partial Order for A Set of Concepts

A partial order used here is a linear sequence of concepts in a *Gap*. With a partial order, the student can learn all the concepts in the *Gap* one by one without dissatisfying the *LOR*. There may be multiple partial orders for a *Gap* and its *LOR*. As introduced in Section 2.4.1, we form a constraint satisfaction problem to find out all possible partial orders as follows:

- Variables: $X = \{x_1, x_2, \dots, x_n\}$, where n is the cardinality of the *Gap*.
- Domains: $\forall_{x \in X}$, the domain of x is $D_x = \{c | c \in Gap\}$.
- Constraints:
 1. $x_i \neq x_j$,
 2. $\forall_{(p,q) \in LOR} \neg \exists_{x_r, x_s \in X} (x_r = q \wedge x_s = p \wedge 1 \leq r < s \leq n)$.

A partial order is one kind of assignment of values from D_x to x for every $x \in X$ without breaking the *LOR*. For a student, concept $x_i \in X$ is the $no.i^{th}$ step to be studied. The partial order can be expressed as $x_1 - > x_2 - > x_3 - > x_4 - > \dots - > x_n$. For example, a student wants to learn a few concepts of rough sets, and the *Gap* = $\{Degree\ of\ overlap, Interpretation\ of\ (\alpha, \beta), Equivalence\ class\ (EC), Approximation\ on\ definable\ set\}$. One partial order is *Equivalence class (EC)* $- >$ *Degree of overlap* $- >$ *Approximation on definable set* $- >$ *Interpretation of (α, β)* .

Student Preference for Customizing Partial Orders

In a concept $C = \{id, N, I, L, Q, P\}$, a set P contains several pairs of (*character*, *character_value*), such as (*difficulty*, *low*). In this case, the *difficulty* is a character of concepts, while the *low* is a value of this character.

Let the set of characters be $Character = \{x | (x, y) \in P\}$, and the domain of a character p is $D_p = \{y | (x, y) \in P \wedge x = p\}$.

Preference is defined by each student, and is used to find a unique partial order from multiple ones. This partial order should satisfy the student's preference most. An item of preference contains two hierarchical priorities, namely, priority of *characters* and priority of *character_value* in each *character*. Priority of *characters* is always satisfied firstly. Besides, priority of *character_value* in each *character* is considered as best it can. The definition of the preference consists of:

- $Pref = \{(p, priority) | p \in Character\}$, where $|Pref| \leq |Character|$. It reflects student preference in the hierarchy of *character*. $\forall_{(p, priority) \in Pref}$, *priority* defines the learning priority of character p in comparison with other characters in *Pref*.

- $PrefDetail_p = \{x_1, x_2, \dots, x_n\}$, where $n = |D_p|$, $x_i \in D_p$, and $x_i \neq x_j$. It reflects student preference in the hierarchy of *character_value* in *character p*. $\forall_{x_i \in D_p}$, the value of x_i defines the learning priority compared with those of others in $PrefDetail_p$.
- The semantic meaning of $Pref$ and $PrefDetail_p$ is described as follows:
 - $SG \subseteq Gap$.
 - SG can be divided into n parts by $Pref$. These parts can be denoted by $SG^{p_1}, SG^{p_2}, \dots, SG^{p_n}$, where $|SG^{p_1}| + |SG^{p_2}| + \dots + |SG^{p_n}| = |SG|$. Concepts of SG^{p_i} ($1 \leq i \leq n$) is the $no.i^{th}$ batch to be studied.
 - SG^{p_i} can be further divided into m parts by $PrefDetail_{p_i}$. These parts can be denoted by $SG_{x_1}^{p_i}, SG_{x_2}^{p_i}, \dots, SG_{x_m}^{p_i}$, where $|SG_{x_1}^{p_i}| + |SG_{x_2}^{p_i}| + \dots + |SG_{x_m}^{p_i}| = |SG^{p_i}|$. Among concepts of SG^{p_i} , $SG_{x_j}^{p_i}$ is the $no.j^{th}$ batch to be studied given ($1 \leq i \leq m$).

Learning Sequence for A Set of Concepts

The learning sequence is a unique partial order which satisfies the preference of a student most. We modify the constraint satisfaction problem as follows:

- Variables: $X = \{x_1, x_2, \dots, x_n\}$, where n is the cardinality of the *Gap*.
- Domains: $\forall_{x \in X}$, the domain of x is $D_x = \{c | c \in Gap\}$.
- Hard constraints:
 1. $x_i \neq x_j$,

$$2. \forall_{(p,q) \in LOR} \neg \exists_{x_r, x_s \in X} (x_r = q \wedge x_s = p \wedge 1 \leq r < s \leq n).$$

- Soft constraints: $Pref$ and $PrefDetail_p$

Variables, domains, and hard constraints of this problem are same with those which are introduced in *Partial Order*. However, soft constraints are added. They are the priorities of $Pref$ and $PrefDetail_p$ in two hierarchies. As described in Section 2.4.1, the hard constraints are mandatory to be satisfied, and the soft ones should be met as best they can.

3.3 System Design

This section presents the technical architecture, the functional architecture, and design patterns used for organizing classes or objects in ORS.

3.3.1 Technical Architecture

A technical architecture describes the separation of components regarding technical issues rather than business logic. Model-view-controller (MVC) has been widely used in designing web applications and conforms to the multi-layer architecture of WLSS [15]. The MVC has evolved to many variations. A passive implementation of MVC neglects notifications between the model component and others (view and controller components), since these notifications are not required or are not supported by software platforms [39]. In the scenario of web applications, a browser is difficult to receive “notify” since it is a classic “pull” mechanism rather than “push”. One of such passive implementations is named “Model 2” [51].

Figure 3.3: Technical architecture of ORS

The technical architecture of ORS is extended from “Model 2” as shown in Figure 3.3. The *View* generates graphical interfaces to users. The *Controller* handles the HTTP request and response between users and the system. The *Model* encapsulates the business logic of ORS. The *Model* is divided into three layers, namely, the *Service*, the *Dao*, and the *POJO*. Each class of the *POJO*, or Plain Old Java Object, represents a table in the *Database*. The *Dao*, or Data Access Object, contains classes which operate data on a single class of the *POJO*. The *Service* encapsulates business logic among multiple classes of the *Dao* and serves the *Controller*.

When a user utilizes a browser to access ORS, the data flow proceeds as follows:

Step 1: a user manipulates on the *Browser*.

Step 2: the *Browser* issues a HTTP request to the *Controller*.

Step 3: the *Controller* receives the request. If its inner business rules are not enough to handle, the *Controller* sends a request to the *Model*.

Step 4: the *Model* sends a query to the *Database* for that request.

Step 5: the *Database* responses corresponding data to the *Model*.

Step 6: the data is processed by complex business rules of the *Model*. The processed information is sent to the *Controller*.

Step 7: the *Controller* makes decision to choose a specific page in the *View*.

Step 8: the specific page equipped with related data is sent to the *Browser*.

Step 9: this page is presented to the user by the *Browser*.

For each request launched by a user, there may be three modes of data flow, namely, the complete mode, the moderate mode, and the simple mode. The complete mode needs data from the *Database* and contains all the steps. In the moderate mode, business rules of the *Controller* and the *Model* are enough to make decision. There is no need to operate data from the *Database*. It only involves Steps 1, 2, 3, 6, 7, 8, and 9. In the simple mode, the inner business rules of the *Controller* is enough to make decision. There is no need to operate data from the *Model* and the *Database*. It only involves Steps 1, 2, 7, 8, and 9.

Since the multi-layer structure and use of browsers conform to the WLSS definition presented in Section 2.3.3, this architecture can be treated as a design of WLSS.

3.3.2 Functional Architecture

A functional architecture describes the separation of components regarding business logic rather than technical issues. As shown in Figure 3.4, the functional architecture of ORS includes four main functional components, namely, the *Expert area*, the *Tutor area*, the *Student area*, and the *Public management area*.

The *Expert area* is designed to input concepts, dependency, and quizzes by experts. In particular, the *Concept* is used to create, read, update, and delete (CRUD) a concept, which contains the name, description, links of research papers, quizzes, and values on characters (e.g., the low on the difficulty character). The *Dependency* CRUD dependent relationships among concepts. The *Quiz* CRUD a question and

Figure 3.4: Functional architecture of ORS

candidate answers for each concept. The *Characters* CRUD a character (e.g., the difficulty) and its details (e.g., low, normal, high).

The *Tutor area* allows human tutors to help learners set up their personal goals, and predicts as well as records student learning time as a virtual tutor. In particular, the *Range* helps tutors CRUD some predefined objectives, and a learner can select one of them as the learner's goal. The *Estimated time* predicts how long a learner may spend to master a particular concept. For each concept, this time may be a value or a combination of values coming from the averages of the best N similar learners, the worst N similar learners, the latest N similar learners, etc. The *Record time* logs the actual learning time spent on each concept. The *Archive* stores the study history of each learner.

The *Student area* provides learners the interaction interfaces with ORS. In particular, the *Personality* is used to maintain student personal information (e.g., age, educational level). The *Goal* CRUD a goal from ranges or concepts. The *Experience* allows a student to mark those concepts which he/she has already mastered in his goal initially. The *Preference* allows students to have some preference (e.g., from low to

high on the difficulty character) on learning sequences without breaking dependency among concepts. The *Study plan* generates a linear study plan based on a goal, experience, and preference. The *My progress* displays how many concepts students have learned and how many remaining concepts. The *Working place* displays content of a concept and quizzes associated with it. The *Modify SP* finds out dependent concepts when a student fails in a quiz, sorts them based on preference, then adds them into the old study plan.

The *Public management area* lets administrators manage the basic configurations of the system. The *Configure* is used to define the menu, its internal links, and parameters of the *Estimated time* (such as the N). The *Role* is used to define how many functions a role could access. *User* manages user roles and basic information (e.g., contact information).

According to the definition of WLSS in Section 2.3.2, the *Expert area* contributes to the function of the *complexity of learning support*, and the *Tutor area* relates to the *Interaction support*. The *Student area* provides functions which are similar with the *Adaptability support* and the *Assessment support*. The architecture can be treated as a design of WLSS.

3.3.3 Design Patterns for Organizing Classes

Design patterns are used to ease the design of programs in each component of the above architectures. They are reusable and empirical templates which define the structures of classes or objects. The main categories of design patterns are creational, structural, and behavioral patterns. In this thesis, two structural patterns are used to develop some functions of ORS, namely, the adaptor and the facade.

Adaptor

An adaptor can help a client program easily access an incompatible class without changing this class and the client [19]. An object is called an adaptor if it satisfies: (1) it provides a method to clients; (2) These clients can not directly access another class for data format or other reasons; (3) The method has a suitable interface to be invoked by those clients; (4) The method encapsulates business logic of invoking that class; and (5) The class (adaptee) is passed into the object as a parameter of the method or a constructor.

One typical application of the adaptor pattern in ORS is the *Dao* which is introduced in Section 3.3.1. There are three layers in the *Model*, namely, the *Service*, the *Dao*, and the *POJO*. According to the architectural style, an object in the *Controller* can only access the *Dao* in order to get data from the *POJO*. An adaptor is required

Figure 3.5: An adaptor pattern for restricting cross-layer accessibility

to satisfy that style.

As shown in Figure 3.5, the client is *RangeAction.java* and the adaptor is *GenericManager.java*. The Adaptee is *GenericDao.java*. Business logic has been encapsulated in methods of the adaptor, such as *save(T object)*. The client is easier to utilize classes in other components. In another case, the adaptor is *GenericDao.java* if *GenericManagerImpl.java* tries to access *SessionFactory.java*.

Facade

A facade is able to help a client program simply access a series of classes through an interface regardless of the dependency among these classes [19]. An object is called a facade if it satisfies: (1) it provides several methods to clients; (2) each method is a simplified and unified interface to operate a set of classes belonging to a class library or subsystem; and (3) No method can be invoked by those classes.

One typical application of the facade pattern in ORS is the *Estimated time* which is introduced in Section 3.3.2. This function utilizes a clustering algorithm from the software package, named weka, to find a group of previous users having similar personality with a new user. It involves steps of data preparation, building model, and executing model. Each step may refer to multiple classes and their dependencies of weka and JDBC. A facade is required to ease the manipulation of classes for client programs.

As shown in Figure 3.6, the client is *PlanServiceImpl.java* and the facade is *ClusterImpl.java*. Others are supporting classes of weka and JDBC. Complex business logic has been encapsulated in two methods of the facade, namely, the *prepareData()* and the *doCluster()*. The client is easier to utilize weka through the two methods.

Figure 3.6: A facade pattern for encapsulating complex business logic

3.4 Implementation

This section introduces algorithms for learning sequences, a mechanism for estimated time, and essential functions of three functional components.

3.4.1 Algorithms for Learning Sequences

One major function of ORS is the *Study plan* which is the core of the adaptation as described in Section 3.3.2. The learning sequence of a study plan is the result of adaptation to preference and performance. The generation of learning sequences varies when dealing with different types of preference. There are two types of preference, namely, preference without relevance and preference with relevance.

Preference without Relevance

When the preference doesn't contain the character of relevance, the *Study plan* uses Algorithm 1 to find a learning sequence for a particular learner initially. A *Gap* contains concepts which are in a learner's goal and not in the experience. The

Algorithm 1: A best-first search for finding a learning sequence

Data: NAC is a priority queue with $h(c)$ as the comparator ;
LOR is useful dependency among concepts ;
Result: a learning sequence
 $PO = \{x_1, x_2, \dots, x_n\};$ // initialization
 $i \leftarrow 0;$
 $NAC.push(\{c3 | c3 \in Gap \wedge \neg \exists_{(c1, c2) \in LOR} (c3 = c2)\});$
while $NAC \neq Nil$ **do**
 $i \leftarrow i + 1;$
 $c1 \leftarrow NAC.pop();$
 $x_i \leftarrow c1;$
 while $existsParent(LOR, c1)$ **do** // when $c1$ is a parent
 $c2 \leftarrow findChildByParent(LOR, c1);$ // return first child
 $LOR.remove((c1, c2));$
 if $!existsChild(LOR, c2)$ **then** // if $c2$ has no parent
 $NAC.push(c2);$ // add into NAC
 end
 end
end
return PO

algorithm assigns all elements of a *Gap* to a learning sequence $\{x_1, x_2, \dots, x_n\}$ regarding dependency and preference. Firstly, the algorithm finds a concept with the highest priority among those concepts which belong to the *Gap* and whose prerequisites do not belong to the *Gap*. Priorities of concepts are determined by the function $h(c)$ based on preference. Subsequently, that concept is assigned to the sequence and is removed from the *Gap*. The dependent relationships which treat that concept as a prerequisite are also removed from the dependency. Moreover, the algorithm repeats the finding, assigning, and removing steps based on the updated *Gap* and dependency until the *Gap* is empty. Finally, each element of the learning sequence has been assigned a unique concept. The definitions of *Gap* and dependency (i.e., *LOR*) are presented in Section 3.2.3. This algorithm mainly depends on the evaluation function $h(c)$ and the priority queue *NAC*.

The evaluation function $h(c)$ determines priorities of concepts in a *Gap* based on preference as shown in Algorithm 2. It is a mapping $Pref, PrefDetail \rightarrow Integer$ for a concept $C \in Gap$. We utilize a decimal integer to express the *Integer*, given $1 < |PrefDetail| < 10$. The fractile reflects the priority of *Pref* from left to right.

Algorithm 2: An evaluation function $h(c)$ for calculating priority of concepts

Data: c is a concept, $c = \{id, N, I, L, Q, P\}$

Result: $h(c)$

$h(c) \leftarrow 0$; // initialization

$Pref \leftarrow orderByPriority(Pref)$;

for $(p, priority) : Pref$ **do**

$p_value \leftarrow findValue(P, p)$; // find character = p , return p_value

$i \leftarrow findIndex(PrefDetail_p, p_value)$; // find $x_i = p_value$, return i

$h(c) \leftarrow h(c) * 10 + (10 - i)$;

end

return $h(c)$

The value in each fractile expresses the priority of *PrefDetail* in its *Pref* from big to small.

The priority queue *NAC* is used to ease the manipulation on a *Gap*. It contains available concepts to be chosen in the finding step of Algorithm 1. These concepts belong to the *Gap* and their prerequisites do not belong to the *Gap*. Since the *NAC* is a queue and has the $h(c)$ as the comparator, the top element in the queue always has the highest priority among its elements. In the assigning step, the top element is removed from the *NAC*. This leads to the result that the dependency is updated and some concepts in the *Gap* may be moved to the *NAC* accordingly.

If a student achieves poor performance in learning a concept by taking its quizzes, for example, the *Gap* will be updated to prerequisites of this concept. A new learning sequence will be generated by invoking the algorithm again. The study plan will be updated based on the new learning sequence.

Preference Containing Relevance

When the preference contains the character of relevance, the *Study plan* uses Algorithm 3 to find a learning sequence for a particular learner initially. The algorithm utilizes a heuristic depth-first search method to assigns all elements of a *Gap* to a learning sequence $\{x_1, x_2, \dots, x_n\}$ regarding dependency and the learner's preference. The definitions of *Gap* and dependency (i.e., *LOR*) are presented in Section 3.2.3.

The algorithm treats a network of concepts (i.e., a *Gap* with its dependency) as a forest including trees. Leaves of trees are concepts which have not parent concepts. Concepts that are not parents of any one are roots of trees. The algorithm searches the forest from roots to leaves in a depth-first way. When a leaf is found, it is

Algorithm 3: A heuristic depth-first search for finding a learning sequence

Data: STK is a stack ;
NAC is a priority queue with **minus** $h(c)$ as the comparator ;
LOR is useful dependency among concepts ;

Result: a learning sequence

```
PO = { $x_1, x_2, \dots, x_n$ };           // initialization
i ← 1;
NAC.push({ $c3 | c3 \in Gap \wedge \neg \exists_{(c1, c2) \in LOR} (c1 = c3)$ }) // root nodes
while NAC ≠ Nil do
  | c1 ← NAC.pop();
  | STK.push(c1);
end
while STK ≠ Nil do
  | c1 ← STK.peak();           // look top object without popping
  | if  $\neg \text{existAsChild}(LOR, c1)$  then           // c1 has't parents
  |   | STK.pop();           // remove from STK
  |   |  $x_i \leftarrow c1$ ;
  |   |  $i \leftarrow i + 1$ ;
  | else           // c1 has parents
  |   | while  $\text{existAsChild}(LOR, c1)$  do           // get all parents
  |   |   | c2 ← findParentByChild(LOR, c1);           // return a parent
  |   |   | NAC.push(c2);
  |   |   | LOR.removeParent(c2);           // del relation of c2 as a parent
  |   | end
  |   | while NAC ≠ Nil do           // push elements of NAC to STK
  |   |   | c2 ← NAC.pop();
  |   |   | STK.push(c2);
  |   | end
  | end
end
return PO
```

assigned to the sequence. After the assignment, the leaf is pruned from the tree, and its connections to other nodes are deleted. Let roots be the lowest nodes and leaves be the upmost nodes. Priority among roots and priority among upper nodes of a lower node are determined by the $h(c)$. The evaluation function $h(c)$ calculates the priority value of each node according to preference excluding the character of relevance.

3.4.2 A Mechanism for Estimated Time

Another major function of ORS is the *Estimated time* described in Section 3.3.2. It estimates the future learning time for each learner to improve learning efficiency. Figure 3.7 shows that a mechanism is used to calculate estimated time of a study plan on concept by concept basis.

For the *previous learners* who have finished learning tasks, their time spent on each concept is recorded as well as their personality (e.g., age, education level, gender). For the *learner A* who starts a learning task, the process of *Cluster analysis* identifies the actual learning time of those previous learners having similar personality with this learner. The basic notion of this process is introduced in Section 2.4.2. In the actual time, each concept has a series of data distributed on different dates. For the sake of simplicity in programming, the averages of the latest N similar learners are chosen to be estimated time. For each concept, the process of *Moving average* calculates the average time from the most recent N pieces of the concept's actual time. Finally, the estimated time of the *learner A* is the result of matching between the learning sequence and those averages.

Figure 3.7: Predict the estimated time for a new learner A

An example is presented to introduce the running of the above mechanism. Suppose *learner A* has configured his personality, goal, experience as well as preference, and his *Learning sequence* contains 6 concepts. After the *Cluster analysis*, 20 *previous learners* are similar with *learner A*. Subsequently, their actual learning time are extracted to the *Historical learning records in that group* through the *Match*. Suppose those actual time involves 68 concepts, and each concept has a series of data distributed on different completion dates. For the sake of simplicity in programming, the *Moving average* calculates averages for all 68 concepts. After the *Moving average*, there are 68 pairs of data in the *Estimated time for each concept*. Each pair contains a concept and the average of its most recent 5 actual time according to completion dates. The process of *Match* picks up 6 pairs from the *Estimated time for each concept* according to concepts in the *Learning sequence* of *learner A*. The 6 pairs are stored in the *Estimated time of learning sequence* and used to generate a study plan for *learner A* later.

3.4.3 Programming Languages and Software Environment

Java and Javascript are the two programming languages implementing ORS. In particular, two Java-based open source systems, appfuse and weka, are used. Appfuse offers the project skeleton which can be used to add new functions by programming quickly [55]. For a classic CRUD function, appfuse is able to easily generate a series of available scripts (e.g., JSPs, a Controller class, parts of XML configuration) from a POJO class, and then programmers can modify these scripts to realize desired details. It can also generate a POJO class from a database table. Some inherent functions of appfuse include authentication, authorization, user management, E-mail,

Table 3.3: Open source softwares used in ORS

Name	Version	Description	URL
Appfuse	2.2.1	Java-based information system	http://appfuse.org
Struts	2.3.7	Web application framework focusing on MVC	http://struts.apache.org
Hibernate	4.1.8	Data persistence framework	http://www.hibernate.org
Spring	3.1.3	Web application framework focusing on application level	http://spring.io
Dojo	1.9.1	Javascript toolkit	http://dojotoolkit.org
DWR	2.0.3	A Java library focusing on AJAX	http://directwebremoting.org
Weka	3.6.6	Data mining toolkit	http://www.cs.waikato.ac.nz/ml/weka

and file upload. Weka provides the APIs of its clustering algorithms to support the *Cluster analysis*, and is used in data pre-processing, clustering, etc [31]. The system is deployed in Tomcat and the database used is MySQL.

Table 3.3 shows the open source softwares used in ORS. Struts, hibernate, spring, dojo, and DWR are also involved in the development. Appfuse has already combined with struts, hibernate, and spring. It provides the infrastructure to realize both the technical architecture and the functional architecture of ORS. Additionally, we integrate weka, dojo, and DWR into appfuse to realize several functions, such as the *Record time* introduced in Section 3.3.2.

3.4.4 Implementation of the Expert Component

This section presents some important graphical interfaces of the *Expert area* component, such as the *Character*, the *Concept*, the *Dependency*, and the *Quiz*. The functional requirement of each interface is described in Section 3.3.2.

Interface of the Character

Characters are used to define soft constraints. Experts can define many characters, and each character has a set of values. Some of these values will be assigned to concepts by experts. A concept contains only one value on each character. Figure 3.8 shows typical characters of concepts. Experts can disable and enable a specific character. Figure 3.9 shows details of a character (e.g., the difficulty). Experts can CRUD its details if necessary.

Figure 3.8: View a list of characters

Figure 3.9: Edit details of a character

Interface of the Concept

Experts can CRUD a concept in ORS. As shown in Figure 3.10, the *Concept* interface presents three parts of information, namely, basic info, characters, and quizzes. Basic info contains the name of a concept, description, and links of related papers or content. Characters identify the detail of each character on that concept. Quizzes

Basic Info

* Name: Logic language

* Description: It is used to describe things in formal way. ...

* Text1: first-order logic on wikipedia

Url1: http://en.wikipedia.org/wiki/First-order_logic

* Text2: Logic Programming

Url2: <http://localhost:8080/editConcept?id=4>

* Text3: Introduction to logic

Url3: http://philosophy.lander.edu/logic/relevance1_quiz.htm

Characters

Difficulty: low

Sub-Subject: unknown

Quizzes

☐ Q1 for test1

☐ Q2 for test1

☐ Q1 for test2

☒

Figure 3.10: Edit a concept

connect specific questions with that concept. A concept can be assigned values of several characters. It has one and only one value on each character.

Interface of the Dependency

An item of dependency is also described as a learning order relationship or a prerequisite. Experts can CRUD an item of dependency. Dependency connects the prerequisite concepts for each concept if such relationships exist. An item of dependency consists of two parts, namely, a parent concept and a child concept. Students

103 Dependencies found, displaying 1 to 25. [First/Prev] 1, 2, 3, 4, 5 [Next/Last]

Id	ParentConId	ParentConName	ConceptId	ConceptName
16	1	Concept	6	Concept in an information table
9	2	Information table	3	Equivalence Relation in Information table
12	2	Information table	4	Logic language
14	2	Information table	5	Means of formula
17	2	Information table	6	Concept in an information table

Figure 3.11: View a list of dependency

are required to master the parent concepts before they learn a child concept. Figure 3.11 shows a list of dependency among rough sets concepts in ORS.

After an expert trying to change an item of dependency, the ORS checks whether or not there is an infinite loop in dependency caused by the change. If not, that change will be stored in the system; Otherwise, the change will be canceled.

Interface of the Quiz

Several quizzes always accompany a concept. Experts create multiple quizzes. A quiz consists of two parts, namely, the question and the answers. The answers include not only the right solutions, but also the wrong ones. Figure 3.12 shows the interface of editing a quiz. For a quiz belonging to choice selection. The question and answers are pictures containing text.

3.4.5 Implementation of the Tutor Component

This section presents some important graphical interfaces of the *Tutor area* component, such as the *Range*, the *Home page*, the *Record time*, and the *Estimated time*. The functional requirement of each interface is described in Section 3.3.2.

* Name: Q1 for logic language

Select a true one from following statements, where the domain is all real numbers.

Browse... No file selected.

+ Add answer

answer	Is solution	action
$\exists x(x^4 < x^2)$	☒	delete
$\exists x(x^2 > x)$	☒	delete
$\forall x((-x)^2 = x^2)$	☐	delete
$\forall x(2x > x)$	☐	delete

Figure 3.12: Edit a quiz

* Name: 60-70 marks

Description: For students who only want pass the final

Status: 2

Concepts in this Range:

- ☒ Concept
- ☒ Information table
- ☐ Equivalence relation (ER)
- ☒ Logic language
- ☒ Means of formula
- ☒ Concept in an information table

Figure 3.13: Define a range from concepts

Interface of the Range

A range points to a set of concepts. Tutors define a series of ranges. With these ranges, it is easier for students to select their learning objectives. Typical ranges in ORS include *60-70 marks*, *70-80 marks*, *80-100 marks*, and *Pursuing excellence*. Figure 3.13 shows the interface of editing a range. Tutor can change the concepts of a range by selecting and canceling them in the concept list.

Interface of the Record Time

The *Record time* is implemented in the *Working place* of the student area. It provides three ways to record the actual learning time spent on a concept: (1) students press the *Pause* button in the *Working place*; (2) students press the *Done* button in the *Working place*; and (3) the ORS automatically records if students ignore the periodical messages.

The system prompts a message to a learner every thirty seconds as shown in

Figure 3.14: Popup message for recording actual study time of students

Figure 3.14. If no action happens, the system supposes that the learner is absent. The time after the notification will not be added. If pressing the *OK*, the system starts to record time again. If pressing the *Cancel*, the system goes to the home page.

Interface of the Estimated Time

The *Estimated time* is a function running in the back scene. It calculates the estimated time for every student by using the mechanism presented in Figure 3.7. The result is used in the *Study plan* to generate study plans for students.

Interface of the Home Page

This is the home page for tutors, as well as experts and students. Figure 3.15 shows the interface. Users can click related links to access different functions.

Figure 3.15: Home page of ORS

3.4.6 Implementation of the Student Component

This section presents some important graphical interfaces of the *Student area* component, such as the *Goal*, the *Experience*, the *Preference*, the *Study plan*, the *Working place*, and the *My progress*. The functional requirement of each interface is described in Section 3.3.2.

Interface of the Goal

A goal contains learning objectives of a student, and includes a set of concepts. There are two ways for a student to define a goal. One way is the student chooses a range from the range list. Another way is the student chooses several concepts directly from the concept list. In this way, the student only has to choose the concepts roughly, and dependent concepts of selected ones will be chosen automatically. When the student chooses *Concept in an information table*, for example, the related seven

-----You could select a Range, which related to groups of Concepts-----

Ranges:

- ☐ 60-70 marks
- ☐ 70-80 marks
- ☐ 80-100 marks
- ☐ Persue excellence

-----Or, you could also select Concepts directly-----

Concepts:

- ☐ Concept
- ☐ Information table
- ☐ Equivalence relation
- ☐ Logic language

Figure 3.16: Set a goal from two ways

Those concepts are what you have selected as target for learning.

7 items found, displaying all items.

Id	Name
1	Concept
2	Information table
4	Logic language
5	Means of formula
6	Concept in an information table
11	Logic connective
17	Set operator

Delete

Figure 3.17: Concepts of a goal

concepts are automatically selected based on dependency.

Figure 3.16 shows the interface of defining a goal. Students can select their goals from ranges or the concept list. Figure 3.17 shows the result after selection in the above example .

Interface of the Experience

An item of experience is a set of concepts which have already been mastered by the student after defining a goal. Suppose the student has known *Logic connective* in the above example.

Figure 3.18 shows the interface of marking concepts as experience. In the example, there are seven concepts in the goal. However, there are only three concepts without prerequisites. The student can mark his experience from the three concepts as shown in Figure 3.18. We assume that the student selects *Logic connective* and clicks the *Next*. The result is shown in Figure 3.19.

After marking the concepts as experience, some items of the dependency may be

Please select the concepts you have known.

Concepts:

☐ Concept

☒ Logic connective

☐ Set operator

☒ Next

7 items found, displaying all items.

Id	Name
1	Concept
2	Information table
4	Logic language
5	Means of formula
6	Concept in an information table
11	Logic connective (known)
17	Set operator

Figure 3.18: Mark concepts as experience

Figure 3.19: A goal with experience

ignored. This leads to the result that other concepts may be available to be marked. The student can mark experience from bottom to top in this way.

Interface of the Preference

Students define preference to personalize their learning sequences. An item of preference has prioritized constraints based on character values on concepts. It consists of two hierarchies, namely, priority of different characters and priority of character values in each character.

Figure 3.20 shows the interface of how to define priority among different characters. Initially, a student can choose 0 or N characters. Subsequently, the student can define the priority by dragging characters up and down. In the example, the *Difficulty* character has higher priority than the *Sub-subject*.

Figure 3.21 shows the interface of how to define priority inside a character. A student can define the priority by dragging values of that character up and down. For example, we click the *modify* button of the *difficulty* character in Figure 3.20. A popup window is highlighted and shows the character's values in Figure 3.21. These values can be dragged. In this case, the *low* has the highest priority, while the

Figure 3.20: Priority among characters Figure 3.21: Priority of character values

unknown is the lowest; the *normal* has higher priority than the *high*.

Interface of the Study Plan

Study plans are the main output of the learning model. It is used to guide learners to study rough sets effectively and efficiently. As shown in Figure 3.22, a study plan mainly consists of two parts, namely, the learning sequence and the estimated time.

Learning Sequence	Concept	Created Date	Updated Date	Estimated Time	Status
001	Set operator	10-06-2014	10-06-2014	12	0
002	Information table	10-06-2014	10-06-2014	18	0
003	Logic language	10-06-2014	10-06-2014	27	0
004	Means of formula	10-06-2014	10-06-2014	12	0
005	Concept	10-06-2014	10-06-2014	16	0
006	Concept in an information table	10-06-2014	10-06-2014	9	0
Total Estimated Time:				94.0	

Figure 3.22: A study plan containing the learning sequence and estimate time

The learning sequence guides students to learn concepts one by one rationally. It has considered dependency among concepts, a student's goal, experience, and preference. The learning sequence is updated if the student achieves poor performance on a quiz. The estimated time tells the learner how long he/she probably requires to study each concept. It helps students schedule learning paces and improve learning efficiency.

Interface of the Working Place

Students learn concepts and take quizzes in the *Working place*. Figure 3.23 shows the interface of how a student learns a concept. The student can study description of the concept and links of content. In the learning period, the student can pause the study by pressing the *Pause* if required. The student can continue to study that concept when available in the future.

-----description-----
 Name: Logic language

Description: It is used to describe things in formal way. ...

-----materials-----
 1. [first-order logic on wikipedia](#)
 2. [Logic Programming](#)
 3. [Introduction to logic](#)

-----Quiz-----
 Question:
 Select a true one from following statements, where the domain is all real numbers.

-----Answers: (please choose 1 as your answer)-----
 $\exists x(x^4 < x^2)$ $\exists x(x^2 > x)$ $\forall x((-x)^2 = x^2)$ $\forall x(2x > x)$

☐ ☐ ☐ ☐

Figure 3.23: Learn and test a concept

Sorry!

Your answer is incorrect.
 Right answers are shown as follows:

$\exists x(x^4 < x^2)$	$\exists x(x^2 > x)$
------------------------	----------------------

For better understanding

Concepts related to this question should be studied again.
 Below is the list of related concepts, and they will be added into your study plan automatically.

1. Information table
2. Logic connective

Figure 3.24: Notification of a failed quiz

After learning a concept properly, the student should take its quizzes by reading their questions and selecting right answers. The student is notified if wrong answers are made in a quiz. Figure 3.24 shows the details of notification. This notification provides not only the quiz's right answers, but also the prerequisites of the concept related to this quiz.

Interface of the My Progress

The progress is generated after a student starting to learn concepts following his/her study plan. It reflects the learner's current learning status. As shown in Figure 4.2, the progress mainly consists of two parts, namely, the finished part and the unfinished part.

The finished part presents concepts which have been mastered by a student. The time spent on learning these concepts is also displayed. The unfinished part shows

This is your current progress. Please continue to finish your job. Or, you could [delete](#) it.

Have finished:

Learning Sequence	Concept	Created Date	Updated Date	Time Spent	Status
001	Set operator	19-02-2014	19-02-2014	12	2
002	Information table	19-02-2014	19-02-2014	18	2

Need to learn:

Learning Sequence	Concept	Created Date	Updated Date	Estimated Time	Status
003	Logic language	19-02-2014	19-02-2014	27	1
004	Means of formula	19-02-2014	19-02-2014	12	0
005	Concept	19-02-2014	19-02-2014	16	0
006	Concept in an information table	19-02-2014	19-02-2014	9	0
Total Estimated Time:				64.0	

Figure 3.25: Progress showing the finished part and unfinished part to a student

how many remaining concepts the student needs to learn in the future. The estimated time is offered to help the student schedule his/her learning paces.

Chapter 4

Demonstrative Examples

This chapter demonstrates how a student gets an adapted study plan based on the student's preference and performance. Firstly, we use a simple example to show adaptation in the whole learning process. Secondly, a complex example illustrates how the learning sequence adapts to preference containing multiple characters. Subsequently, a comparison between ORS and some existing Web-based learning systems is presented.

4.1 Adaptation in the Whole Learning Process

In this section, we illustrate when and how adaptation to preference and performance is made. The learning objective is only one concept. The preference chosen contains only one character.

4.1.1 Planning with Preference and Estimated Time

Suppose a student wants to learn a specific concept, called *Concept in an information table*. When the student chooses *Concept in an information table* in ORS,

Figure 4.1: Effect of experience and preference on a goal

the related 7 concepts are automatically selected based on the dependency. These concepts, the dependency, and their difficulty levels on the difficulty character are shown in Figures 4.1 (a). We assume that the student has known *Logic connective* and marks it as the experience. What the student needs to learn are the 6 concepts presented in Figures 4.1 (b).

Adaptation to preference is highlighted in Figures 4.1 (c). Before applying the preference, there are multiple available learning sequences. After the student selecting and configuring the character of difficulty as preference (e.g., from low to high), there is only one learning sequence left.

A study plan is generated by ORS for the student as shown in Table 4.1. The

Table 4.1: A study plan including a learning sequence and estimated time

Learning Sequence	Concept	Estimated Time (minutes)
001	Set operator	12
002	Information table	18
003	Logic language	27
004	Means of formula	12
005	Concept	16
006	Concept in an information table	9
Total:		94

learning sequence and the estimated time are presented in different columns. The learning sequence helps the student learn rationally. The estimated time is helpful to schedule the student's learning paces and improve learning efficiency, since it can help the student decrease interruption caused by time shortage in learning a concept.

4.1.2 Learning Sequences Adapted to Performance

Based on the above study plan, we assume that the student has learned the concepts of *Set operator* and *Information table* successfully. The progress is shown in Figure 4.2. The finished part lists the above 2 concepts, while the unfinished part

This is your current progress. Please continue to finish your job. Or, you could [delete](#) it.

Have finished:

Learning Sequence	Concept	Created Date	Updated Date	Time Spent	Status
001	Set operator	19-02-2014	19-02-2014	12	2
002	Information table	19-02-2014	19-02-2014	18	2

Need to learn:

Learning Sequence	Concept	Created Date	Updated Date	Estimated Time	Status
003	Logic language	19-02-2014	19-02-2014	27	1
004	Means of formula	19-02-2014	19-02-2014	12	0
005	Concept	19-02-2014	19-02-2014	16	0
006	Concept in an information table	19-02-2014	19-02-2014	9	0
Total Estimated Time:				64.0	

Figure 4.2: Learning progress reflecting how many concepts are mastered and left

This is your current progress. Please continue to finish your job. Or, you could [delete](#) it.

Have finished:

Learning Sequence	Concept	Created Date	Updated Date	Time Spent	Status
001	Set operator	19-02-2014	19-02-2014	12	2
002	Information table	19-02-2014	19-02-2014	18	2

Need to learn:

Add dependencies of "Logic language into study plan

Learning Sequence	Concept	Created Date	Updated Date	Estimated Time	Status
003.001	Information table	19-02-2014	19-02-2014	14	0
003.002	Logic connective	19-02-2014	19-02-2014	4	0
003.999	Logic language	19-02-2014	19-02-2014	32	1
004	Means of formula	19-02-2014	19-02-2014	12	0
005	Concept	19-02-2014	19-02-2014	16	0
006	Concept in an information table	19-02-2014	19-02-2014	9	0
Total Estimated Time:				87.0	

Figure 4.3: Adaptation to performance leading to the increase of unfinished part

contains the left 4 concepts. Subsequently, the student starts to learn *Logic language* but fails to pass its quizzes.

In this case, adaptation to performance is made due to the failure. The ORS notifies and directs the student to learn the prerequisite concepts of *Logic language* again, namely, *Information table* and *Logic connective*. These two concepts are added into the study plan as shown in Figure 4.3. By observing the difference of values in the first column, the student knows which concepts have been added.

From this example, the student can learn rough sets rationally and efficiently with the adapted study plan, which is updated according to preference and performance in the whole learning process.

4.2 Adaptation to Preference Containing Multiple Characters

In this section, we illustrate adaptation to preference having multiple characters. The learning objectives are two irrelevant concepts. The preference chosen contains

two characters.

4.2.1 Defining Multiple Characters as Preference

Suppose a student wants to learn two irrelevant concepts, namely, *DTRS* and *Reduct using DM* (Discernibility matrix). When the student chooses the two concepts in ORS, the 24 concepts are automatically selected based on the dependency.

Figure 4.4: Related concepts of *DTRS* and *Reduct using DM*

1. Relevance:
unknown ---- modify remove

2. Difficulty:
low > normal > high > unknown ---- modify remove

Figure 4.5: Preference containing multiple characters

These concepts, the dependency, and their difficulty levels on the difficulty character are shown in Figure 4.4. The concepts connected to *Reduct using DM* are isolated from the concepts related to *DTRS*. We also assume the student doesn't have any experience on those concepts.

We assume that the student selects the characters of relevance and difficulty as preference. As shown in Figure 4.5, the student defines that the relevance character has higher priority than the difficulty. This leads the learning sequence's generation to satisfy the relevance character firstly. After the relevance being satisfied, the difficulty character is considered as best it can.

The relevance character leads the system to sort a series of concepts by using a dept-first strategy. It only has one value (i.e., the *unknown*) which does not require to be configured. We treat a set of concepts with dependency as a forest including trees. Leaves of trees are concepts which have not parent concepts, such as *Binary relation (BR)* in Figure 4.4. Concepts that are not parents of any one are roots of trees, such as *Reduct using DM* and *DTRS* in Figure 4.4. Let roots be the lowest nodes and leaves be the upmost nodes. A leaf always has higher priority than its lower node. After a leaf is assigned to the sequence, the leaf is pruned from the tree as well as its connections. The search backs to the leaf's (former) lower node, and continues to find and prune other leaves of this node. If no leaf exists, that node becomes a leaf

Table 4.2: A study plan adapted to preference containing multiple characters

Learning Sequence	Concept	Estimated Time (minutes)
001	Discernibility matrix (DM)	9
002	Matrix absorption	15
003	Minimum DM	14
004	Simplification	11
005	Reduct using DM	16
006	Set operator	12
007	Information table	18
008	Decision table	8
009	Logic connective	5
010	Logic language	27
011	Means of formula	12
012	Definable set	10
013	Family of definable set	10
014	Approximation on definable set	11
015	Partition of universe	11
016	Binary relation (BR)	19
017	ER based on BR	6
018	Equivalence class (EC)	20
019	Degree of overlap	13
020	Interpretation of (α, β)	18
021	PRS	11
022	Bayesian decision procedure	21
023	Bayesian decision procedure on PRS	22
024	DTRS	41
Total:		360

and will be assigned and pruned.

The difficulty character leads the system to rank a series of concepts according to their difficulty levels. These levels include the *low*, the *normal*, the *high*, and the *unknown*. The student can configure an order of those levels. In this case, the student defines the order as *low* > *normal* > *high* > *unknown*. It means concepts with the level of *low* have the highest priority and the *unknown* leads to lowest priority.

A study plan is generated by ORS for the student as shown in Table 4.2. The

learning sequence is the result of adaptation to preference with both the relevance character and the difficulty character.

4.2.2 Analysis of Learning Sequences

We find related concepts are ordered together from the learning sequence in Table 4.2. For example, the concepts related to *Reduct using DM* are supposed to be studied firstly. Steps from 001 to 005 guide the learning of *Reduct using DM*. Steps from 006 to 024 guide the learning of *DTRS*. The separation of two group steps is the result of the relevance character. Without choosing that character, the steps of two group concepts may interlace although the dependency is satisfied. For example, *ER based on BR* may be the next step of *Discernibility matrix (DM)*.

We also find the effect of the difficulty character after the relevance being satisfied. For example, the concepts of *Reduct using DM* are supposed to be studied priori to those of *DTRS*. In terms of the difficulty character, *Reduct using DM* has a level of *normal*, and has higher priority than *DTRS*. In another example, the concepts of *PRS* are supposed to be studied earlier than those of *Bayesian decision procedure*. Steps from 009 to 021 guide the learning of *PRS*. Step 022 is for the learning of *Bayesian decision procedure*. Both *PRS* and *Bayesian decision procedure* are prerequisite concepts of *Bayesian decision procedure on PRS*. Their difficulty levels make that priority.

From this example, the student can select and configure multiple characters as his/her preference. With this capability, the student is able to personalize the learning sequence in more ways.

4.3 Comparing ORS with Existing Systems

The features of ORS can be highlighted by comparing with the 7 existing Web-based learning systems for computer science subjects. The comparison was performed by investigating system functions according to the definition of WLSS introduced in Section 2.3.2. The following 4 main functions of WLSS and their details were reviewed to make such comparison.

1. Complexity of learning support : Supporting complex learning actions and tools, including ontology, simulator, practice, game, multimedia, and estimated time.
2. Adaptability support : Sequencing learning materials due to learner data including goal, experience, preference, and performance.
3. Interaction support : Communication forms between learners and systems, including annotation, asking questions, feedback, and collaboration.
4. Assessment support : Methods of evaluating learner understanding, including exercise and test.

Table 4.3 shows the difference between ORS and existing Web-based learning systems. The row header indicates the 4 main functions for comparison, and the column header corresponds learning subjects of the 7 existing systems as well as ORS. Each data cell indicates what detail functions a system has on a particular main function.

The system for artificial intelligence addresses the 4 main functions evenly. Systems for theory of computation, robotic, and information retrieval emphasize the complexity of learning support. The system for system analysis emphasizes both

Table 4.3: Comparing ORS with existing systems for computer science subjects

Subjects	Complexity of learning support	Adaptability support	Interaction support	Assessment support
Theory of computation [34]	Ontology		Feedback	
Theory of computation [21]	Simulator Practice Game	Goal	Feedback Collaboration	Exercise
Artificial intelligence [33]	Practice	Goal	Feedback	Exercise
Robotic [26]	Simulator Practice Multimedia	Goal	Feedback	Exercise
Network security [49]	Ontology	Goal Experience Preference	Feedback	Test
System analysis [8, 48]	Game Multimedia	Goal	Annotation Feedback	Test
Information retrieval [22]	Simulator Multimedia	Goal	Feedback	
Rough sets (ORS)	Multimedia Estimated time	Goal Experience Preference Performance	Collaboration Feedback	Test

the complexity of learning support and the interaction support. Both ORS and the system for network security emphasize the adaptability support. However, the ORS improves this feature by considering student performance and providing queries on multiple concepts. Besides, the ORS offers estimated time for students to schedule their learning paces and improve learning efficiency.

Chapter 5

Conclusion

This chapter overviews this research, summarizes the contributions, and proposes some future research directions.

5.1 Concluding Remarks

The Web is capable to provide global accessibility and learner-friendly interfaces. Web-based learning offers several advantages compared to traditional learning environments. In post-secondary education, some Web-based learning systems have been built for computer science subjects. However, there are no such systems for rough sets in the literature.

The goal of this research is to design and prototype a Web-based learning support system, named Online Rough Sets, for rough sets. The WLSS offer Web-based learning environments for teachers and students in education. A student-centered learning approach, andragogy, is suitable to rough sets learners in terms of their age. With a learning model based on that approach, learner goals, experience, preference, and performance are considered by the system in the learning process.

Online Rough Sets supports students to learn the subject in a student-centered learning environment through the Web anytime and anywhere. Moreover, it addresses some limitations found in existing systems to provide personalized study plans to help students learn rationally and efficiently. In addition, this system can be used to learn other subjects by changing learning materials through its graphical interfaces.

5.2 Summary of Contributions

The following is the summary of contributions.

1. Identified a hierarchical structure for rough sets concepts

The content of ORS was mainly developed from notes, assignments, and exams of a graduate course (CS836) offered at the University of Regina. Based on these materials, we identified a set of concepts with a hierarchical structure, and collected a set of concept-specific quizzes. These concepts were used as learning topics for rough sets. The hierarchical structure contained learning order relationships among concepts, which define prerequisites for each concept. Performance on a quiz indicated student understanding of its related concept. With such hierarchical structure, the concepts and quizzes were applied to ORS as dependent learning materials which would be appropriate to serve different levels of learners.

2. Developed a student-centered learning model for rough sets learners

As a student-centered learning approach for adults, andragogy was chosen and reviewed since most of rough sets learners were adults. The eight-step learning process of andragogy was used to develop a learning model for those learners.

The learning model was designed to generate adapted learning sequences for each learner according to the goal, experience, preference, and performance. These personalized learning sequences were used to guide learners to study concepts from bottom to top with satisfying the learning order relationships among concepts. Components of the model were defined and formulated.

3. Proposed a mechanism to estimate learning time

The idea of estimating future learning time for each learner is to schedule learning paces. By offering a time slot for each concept, the estimated time is helpful for a learner to allocate proper time to study the concept. A mechanism with cluster analysis and moving average algorithms was proposed to generate the estimated time. For each new learner, the cluster analysis identified the actual learning time of those previous learners having similar personality with this learner. In the actual time, each concept had a series of data distributed on different dates. For each concept, the moving average calculated the average time from the most recent N pieces of the concept's actual time. Averages were presented to the new learner as time slots in a study plan.

4. Built a prototype system with the learning model

A prototype of ORS was built with the learning model and the mechanism for estimated time. Two Java-based open source systems, appfuse and weka, were used in implementation. Appfuse offered the project skeleton and weka provided the APIs of its clustering algorithms. After implementation, the dependent learning materials were input into the system. Two demonstrative examples were performed to show how the system worked and what study plans were

generated after adaptation. In these examples, adapted study plans were helpful to improve learner effectiveness and efficiency in learning rough sets.

5.3 Future Research

An empirical study on ORS is a direction of future research. We plan to utilize the system in future rough sets graduate classes to further evaluate its effectiveness and efficiency. The students can be divided into two groups. One group utilizes ORS to supplement their study, while the other group only depends on the lectures. The final scores of the two groups can be analyzed to examine the effectiveness of ORS.

Another direction is to improve the accuracy of estimated time. The estimated time is predicted by clustering and moving average algorithms from actual learning time. After being used by many learners, the ORS can store the difference between actual time and estimated time as samples of a training set. These samples may lead to the change of algorithm profile for reducing such difference for new learners.

Mouse movement tracking may be applied to record the actual learning time of each concept. The ORS roughly logs the actual time through a mechanism combining text notification and student confirmation. Enhanced by mouse movement tracking, the system may have better opportunity to know whether or not students are learning the subject. This may result more accurate actual time as well as estimated time.

A mobile interface for ORS can be considered for the sake of usability. The presentation layer is originally designed to fit the size and operation behaviors of browsers on PCs and laptops. It may cause some problems when being accessed through a mobile. Since the number of mobile devices keeps on increasing, some learners would prefer mobile devices when using the system.

Finally, I hope this research is beneficial to people in the community of rough sets, especially graduate students and junior researchers.

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