國立交通大學

資訊科學與工程研究所

碩 士 論 文

合作式角色扮演學習架構之設計

The Design of Collaborative Role-Playing Learning Scheme

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中 華 民 國 九 十 七 年 六 月

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摘　要

傳統上對於自然科學領域科學教育的學習，如何評量「問題解決能力」或是「科學探究能力」是一個很有挑戰性的問題，而評估較簡單的科學的知識則是依賴於紙筆測驗。在本篇論文中，我們的目標是建立一個角色扮演學習平台–"The Banana Farm(香蕉農場)"，來透過合作式的水果種植和銷售環境，來強化對自然科學知識理解的學習。為了要達到評量的目的，我們的想法是根據一個多階段圖來設計學習平台不同階段的互動劇情，而在其中的每一個頂點代表學生的動作和決策評估過程。因此，在多階段圖上的不同路徑選擇可以視為科學探究的過程。另外，由於可以重複解決發生的事件，所以在同一階段可以有自身的迴圈表示可以執行很多次，此外，由於要記錄環境狀態與改變可選擇決策，某些路徑上會有規則且有一個額外的暫存記憶體，因此，我們提出一個改良式多階段圖透過學生選擇不同的路徑來幫助科學探究的評量；接下來，我們提出一個合作式學習模式探勘演算法來探勘學生不同的選擇路徑以找出學生常見的互相合作的行為與模式，最後，我們找了 47 組國中程度的學生來做實驗，找到四種不同的合作模式並討論其結果。

關鍵字:角色扮演，遊戲，數位學習，評量，資料探勘，多階段圖

The Design of Collaborative Role-Playing Learning Scheme

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Abstract

Traditionally, the assessment of the high level knowledge about science such as problem solving or inquiry process is a challenging issue. In this thesis, we aim to develop a Role-Playing Learning platform called "*The Banana Farm*" to support the assessment of the nature science learning with collaborative fruit planting and marketing scenario. Traditionally, the assessment of the knowledge about science is relied on the Paper-and-Pencil Test for primitive knowledge level. To support the assessment for inquiry process, our idea is to design the learning platform based on the multi-stage graph model in which the stages of vertices represent the student's actions and decision making during the assessment. Thus, the paths chosen to perform can be seemed as the science inquiry processes of them. Since the actions of the same stage may be executed several times for the assessment of problem solving when some event occurs, the model is extended to have self edge. Besides, the environmental status and the effectiveness of the learning objects are also extended by the working status and constraint rules in each stage. Thus, the extended Modified Multi-stage Graph (MMG) is proposed to support the assessment of inquiry process by the portfolio paths chosen in different stages. Next, the portfolio is used for the collaborative behavior mining to discover the students' frequent collaborative action and interaction patterns during the learning. Combining with the thinking style [18] characteristics of students, the assessment of teams with problem solving and scientific inquiry skills can be obtained. Finally, the experiment on 47 teams from junior high school students has been done and the research shows that four different collaborative behavior patterns has been found and discussed.

Keywords: role playing learning, game, e-Learning, assessment, data mining, multi-stage graph

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Chapter 1. Introduction

In the Scientific Literacy education domain, there are multiple knowledge dimensions such as science as inquiry, science content, science and technology, science in personal and social perspectives, history and nature of science, unifying concepts and processes, etc. [14]. Traditionally, the assessment of the knowledge about science is relied on the Paper-and-Pencil Test which is suitable for the primitive knowledge level or comprehension level. However, the assessment for the advanced skills such as problem solving, inquiry, or social perspectives is a difficult issue.

With the growing of learning technologies, the Role Playing Learning (RPL) [15], in which student takes the role of a person and experiences the impacts of the role with predefined situations, is usually applied to augment the curriculum and motivate real-world skill learning. Role-playing which emphasizes the “real-world” side of science is both interesting and useful to students. Role-playing can challenge students to deal with complex problems with no single "right" answer and to use a variety of skills beyond those employed in a typical research project. In particular, role-playing presents the student a useful opportunity to learn the course content.

To enhance the learning impacts of the RPL, the game platforms or simulation system technologies were applied in several researches[1] to not only give assessment to the students but also replay the process.

In this thesis, we aim to develop an RPL platform called “*The Banana Farm*” to support the assessment of the nature science learning with collaborative fruit planting and marketing scenario, as shown in Figures 3.2(a)(b). Each collaborative group consists of two students who play as employees together operate the same company. To motivate the discussion during the science inquiry, students in the same team which with shared money and harvest can work collaboratively with other team members by participating different role and in charge of different job. As we know, Bloom's Taxonomy [2] is a multi-tiered model of classifying thinking according to six educational objectives, where comprehension is one of the important intellectual abilities, including understanding the meaning, translation, interpolation, and interpretation of instructions and problems. Through the process of playing a role in the platform, the educational objective can be achieved by interacting with the environment objects and other roles. However, it raises another technical issue of how to discover and analyze the behaviors or intentions of the students from the portfolio and how to discover the possible causal relations of behaviors.

To solve issue above, our idea is to provide a collaborative learning platform with stages of scenario and predefined actions in each stage to reveal the collaborative problem solving or science inquiry processes of students based on indicators for scientific education. Thus, from a banana was planted and grown to harvest and sold, the behavior of students are modeled as sequence of decisions. Therefore, with the designed farming and marketing scenario based upon a tradeoff between individual profits or group profits and the indicators, the assessment of the problem solving and science inquiry can be possibly obtained from the way they collaborate to each other.

Accordingly, the **Staged RPL Scheme (SRS)** is proposed, including Learning Design Phase, Enviornment Implementation Phase and Behavior Assessment Phase. In the first phase, our proposed **Modified Multi-stage Graph (MMG)** model can be used to define the environment and actions by means of designing each stage. In the second phase, frame knowledge representation with stereotype slots/values and event driven stored procedure is proposed to implement the environment. In the third phase, we propose a **collaborative behavior mining algorithm** to discover the frequent sequence of decisions. The discovered behavior patterns can have be interpreted meaningfully based on MMG to reveal the possible learning thoughts of students.

Finally, the prototype system has been implemented and several experiments have been done. We take 47 teams from junior high school students with different thinking style characteristics combination. Each team composed of two students. The experiment results and findings of different problem solving and scientific inquiry skills were presented with the thinking style characteristics of students. The research shows that four different collaborative behavior patterns has been found and discussed.

Chapter 2.Related Work

2.1 Role-Playing Learning Systems

In traditional RPL, student takes the role of a person and experiences the impacts of the role with predefined situations. It is helpful for learning [15][9]. With the growth of learning technology, the assessment and the replaying process for RPL becomes popular gradually [13][12][16][17][11][5]. Also, the interest surrounding gaming in education has waxed and waned several times over recent years [1][5][6][8][16]. It is reasonable for student playing role in interactive game environment. In [13], a web-based role-playing simulation generator was proposed to generate web-based role-playing scenario for student to use. However, it is hard to understand students' intention because they could link to other web pages without any intervention. Lee [5] have mentioned that it is possible to use different web-based Interface for students with different cognitive style having their own learning preferences. But the above problem still remains unsolved.

2.2 Game to Learning

In [16][17], the Farmtasia game contains knowledge points from geography, biology, chemistry, technology and economics. An important feature of Farmtasia is that all players' actions and activities in the game are logged. This feature allows teacher to observe and understand students' progress and to extract interesting scenarios from the game proceedings as case studies for class discussion and reflection purposes. The multiplayer nature of the gaming platform ensures the composition of complex and often unique game scenarios as a result of collective behavior of all players.

In [22], a simulation-based learning environment, the Fish Tank System was proposed to model the nitrogen cycle in an aquarium based upon a multi-agents approach, where components of the underlying model can be inspected through exploration and everything in the tank must be defined in advance.

The game [11] based on the Chinese folk legend-24 filial piety stories blends the ideas of RPG and theory of Problem-Based Learning to situate student in different problem, leads the players to develop their learning strategy, and strengthens their problem solving ability.

Even though the games mentioned above can be used for education, most of them are entertainment-oriented or performance-oriented. Futhermore, it is difficult to understand the intentions based on collected data mentioned above.

2.3 Behavior Assessment

Tan[12] mentioned that the environment should include formative assessment methods to allow learners to monitor their learning and enable them to correct their mistakes and misconceptions, and ”*Challenge Zone quiz*” with a dynamic assessment mechanism was provided for students for evaluating the students’ understanding of ecosystem behavior.

Desurvire[8], who used replays of *StarCraft* games to analyze player strategies in terms of building order and player use of keyboard controls and hot key. In [3], proposed a formative assessment approach to integrating six computational intelligence schemes using statistical method and data mining techniques, i.e., the statistic correlation analysis, fuzzy clustering algorithm, the grey relational analysis, K-means clustering scheme, fuzzy association rule and fuzzy inference to identify the key formative assessment rules based on the web-based learning portfolios of an individual learner.

Su[21] proposed a framework of learning portfolio mining, including four phases, User Model Definition Phase, Learning Pattern Extraction Phase, Decision Tree Construction Phase and Activity Tree Generation Phase. In addition, Chen [3][5] applied decision tree and data cube techniques to analyze the learning behaviors of students and discover the pedagogical rules on students' learning performance from web logs including the amount of reading article, posting article, asking question, login, and etc. According to their proposed approach, teachers can easily observe learning processes and analyze the learning behaviors of students for pedagogical needs.

However, although the previously proposed approaches can observe and analyze the learning behavior of students, the intention and the reasons of doing these actions still need to be analyzed.

Chapter 3. Staged Role-Playing Learning (RPL) Scheme

As mentioned before, we have to discover students' behavior before making assessment for them. Therefore, the following two issues should be solved: (1) how to analyze the intentions of the students' behaviors from the portfolio, (2) how to discover the relations of behaviors.

The idea for solving this problem is to design a well-defined learning environment consisting of a sequence of stages so that students can act as a role choosing one from a set of predefined actions in each stage. Based upon this idea, the **Staged RPL Scheme (SRS)** is proposed. SRS has three phases including Learning Design Phase, Enviornment Implementation and Behavior Assessment Phase. In the first phase, our proposed **Modified Multi-stage Graph (MMG)** model can be used to model the environment conditions and available actions in different stages, and to model the available actions affected by the previous decisions with the edges between stages. In the second phase, since the environmental objects are usually inherited from stereotyped knowledge features, the frame knowledge representation with stereotype slots/values and event driven stored procedure is proposed to implement the environment. In the third phase, to support the analysis of students' portfolio for adaptive learning, the **collaborative behavior mining algorithm** is proposed to discover the frequent sequence of decisions. The discovered behavior patterns can be interpreted meaningfully based on MMG to reveal the possible thoughts of students.

The detail of the three phases will be described in Chapter 3.

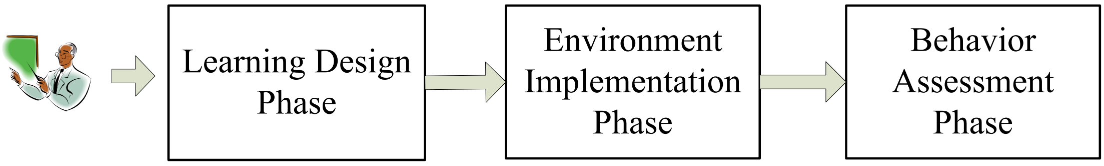


Figure 3.1 Staged RPL Scheme

3.1 Learning Design Phase

3.1.1 "*The Banana Farm*" platform

According to the Staged RPL Scheme we proposed, we develop an RPL platform called "*The Banana Farm*" to support the assessment of the nature science learning with collaborative fruit planting and marketing scenario. Students in the same team which with shared money and harvest can work collaboratively with other team members by participating different role and in charge of different job. The screen shots are shown in Figures 3.2(a)(b).

(a) Farm scene

(b) Market scene

Figure 3.2 Screen shots of "*The Banana Farm*"

In the farm scene, there are several actions could taken such as sowing, feeding, etc. In the market scene, students could take actions such as selling, ordering, etc. Accordingly, the students' behavior can be modeled as a sequence of decisions for action selection. Students may take different roles with different behaviors in this platform. The assessment scenario consisting of two scenes are introduced as follows.

- The farming scenario design for problem solving and science inquiry assessment

The first scenario design is to let the student realize "the balance of soil status and demand". In farm, soil status and marketing demand are two key points. The soil status would be barren if growing too much. If selling banana of high quality to the market, the market demand will increase, otherwise it will decrease. Therefore, how to tradeoff the quantity and quality depends on students' thoughts. If the student could create more profit among the scenario, it might create the win-win scenario together with the farm environment.

- The marketing scenario design for problem solving and science inquiry assessment

The second scenario is to let student realize the "brand-consciousness", which means the student may refer to the banana type, quality and market status for market targeting. The banana of high quality is much difficult to grow than that of low quality, but with high profit. If selling high quality banana continually, the market brand will increase, otherwise it will decrease. Therefore, how to tradeoff the quality and marketing brand depends on students' thoughts. If the student could create more profit among the scenario, it might create the win-win scenario together with the market environment.

3.1.2 Modified Multi-stage Graph Model

We propose a Modified Multi-stage Graph (MMG) model to represent each mission of each stage of the game for three reasons. First, Angelides[1] has mentioned that through a sequential decision-making exercise whose basic function is to provide an artificial but realistic environment that enables players to experience the consequences of their decisions through immediate response. Second, to support choosing next actions easily, it is suitable for having static actions at each stage. Third, due to making assessment for problem solving and scientific inquiry, it is required to define the actions and edges in advance for analyzing the meaning of the behaviors. Thus, we use the multi-stage graph to model the observation mentioned above. The definition for multi-stage graph is as follows.

To simplify our discussion, assume there are k disjoint sets in the rest of this thesis.

Definition 1. Multi-stage Graph[7]

A multistage graph G=(V, E) is a directed graph in which the vertices are partitioned into k ($k > 1$) disjoint sets V_i, $1 \le i \le k$.

- If <u, v> is an edge in E then $u \in V_i$ and $v \in V_{i+i}$ for some i, $1 \le i \le k$.
- $|V_1| = |V_k| = 1$.
- Each set V_i defines a stage in the graph.

To meet the requirements of assessment scenario in Section 3.1.1, some extensions shown below are proposed:

Extension 1: Static edges and choices in each stage for different tradeoff.

Each stage in the graph model has several static edges. Students have to make decisions base on their current status. We can consider that each decision is a tradeoff point. Different decisions could bring out different thought in student's mind.

Extension 2. Weight on edges for different cost and effort.

Each edge should have weight, which means cost or profit. The student can choose one of the weights based on their user status.

Extension 3. Self-loop on some stages for actions repeatedly.

Some stages should have self-loop; because some events may happen suddenly, the student can take some actions several times for solving events, which means some stages should have self-loop.

Extension 4. Rules on some edges for different choices

Some edges could have rules; it mean the edges could be disabled or not depending on the student's actions or choices.

Extension 5. Working memory for recording status.

There is a working memory to record the global or local status. The status is affected by students' actions.

To implement the above extension, a Modified Multi-stage Graph model is proposed below:

To simplify our discussion, assume there are k disjoint sets.

Definition 2. The Modified Multi-stage Graph (MMG)

A modified multistage graph MMG=(V, E) is a directed graph in which the vertices are partitioned into k ($k > 1$) disjoint sets V_i, $1 \leq i \leq k$.

- E= (<u, v>, t, c, r) is an edge in E where vertices $u \in V_i$ and $v \in V_{i+1} \cup V_i$ for some i, $1 \leq i \leq k$, and t means the frequency when $u \in V_i$ and $v \in V_i$; the action execution cost c where $0 \leq c \leq 1$. The constraint rule r is with the format "*if <environment condition> then <enable or disable action v>*". For the pseudo starting stage V_0 and finish stage V_{k+1}, $|V_0| = |V_{k+1}| = 1$.
- Each set V_i defines a stage in the graph.
- Extra working memory can be provided for each stage's status information.

In the following example, The MMG model of "*the Banana Farm*" consists of seven stages, where *r* or *c* associated with the edge represent for rule and cost respectively. There are four stages for farming and three stages for marketing, and a work memory for recording status.

Example 1. The MMG model of the game "*the Banana Farm*"

As shown in Figure 3.3, there are seven stages in the game "*the Banana Farm*". In each stage, there are several predefined actions which can detect the meaningful behavior and inquiry process of students.

- Stage 1: Banana Types Selection (BTS): "*A*", "*B*" and "*C*" are three types of banana to choose, ordered by decreasing profit or decreasing cost. The student can choose the most suitable type depending on the working memory status.

- Stage 2: Field Sowing (FS): "*Fallow*", "*Plant*" and "*Barren*" are three types of soil for when sowing to field. When the soil status is "*Barren*", the r_1 appeared in red color means "*if <soil status is Barren> then <disable action Fallow and Plant>*".

- Stage 3: Disaster Problem Solving (DPS): For growing bananas and weed-grown event or insect event on bananas, there are five farming actions could be chosen, including "*Remove Weed*", "*Terminate Insect*", "*Weedicide*", "*Pesticide*", "*Feed*" and "*null*", where "*Remove Weed*" and "*Terminate Insect*" actions mean removing weed and terminating insect by hand respectively, "*Weedicide*" and "*Pesticide*" actions mean removing weed and terminating insect by marathon, "*Feed*" action means feeding banana, and "*null*" action means the student pass the stage without doing any meaningful action. The student could solve the events by taking "*Remove Weed*" or "*Terminate Insect*" action or feed bananas by taking "*Feed*" action more than once. Thus, the self-loop edge (appears in blue line) to the same stage is added and the t_i means the self-loop times for each action *i*.

- Stage 4: Harvest Timing Selection (HTS): For harvesting the banana, there are three types of choices, which are "*Mature*", "*Early-ripe*", "*Overripe*" and "*Dead*" for the student to choose.

- Stage 5: Product Selection (PS): "*Organic Fruit*", "*Normal Fruit*" and "*Defective*" are three kinds of banana for selling. It may depend on market status or user status in working memory.

- Stage 6: Marketing Strategy (MS): There are two types of strategy for marketing. To make the selling price higher, the student can promote the "*Customer Price Index*" in market status by choosing "*Promotion*" action. To make the market brand of export in market brand status increasing faster, the student can take three kinds of export order, which are large, medium and small order. The r_2 appeared in red color means "*if <(Market status).Order is large> or <(Market status).Order is medium > or <(Market status).Order is small> then < enable Export>*"

- Stage 7: Target Marketing (TM): "*Self Market*", "*Export*" and "*Processed*" are three markets for selling. The selection is usually based on market status because of market brand.

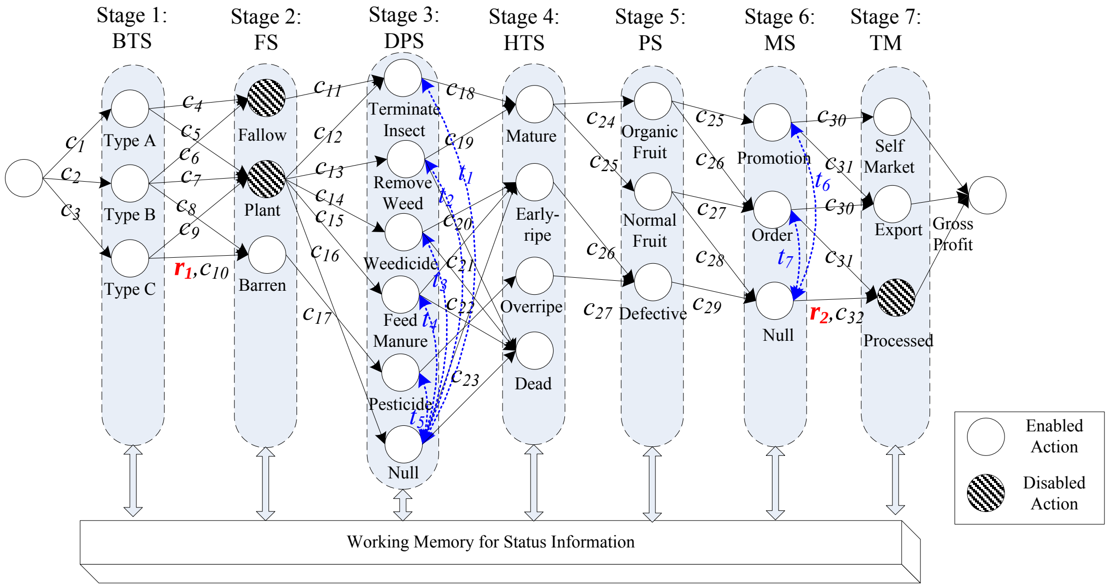
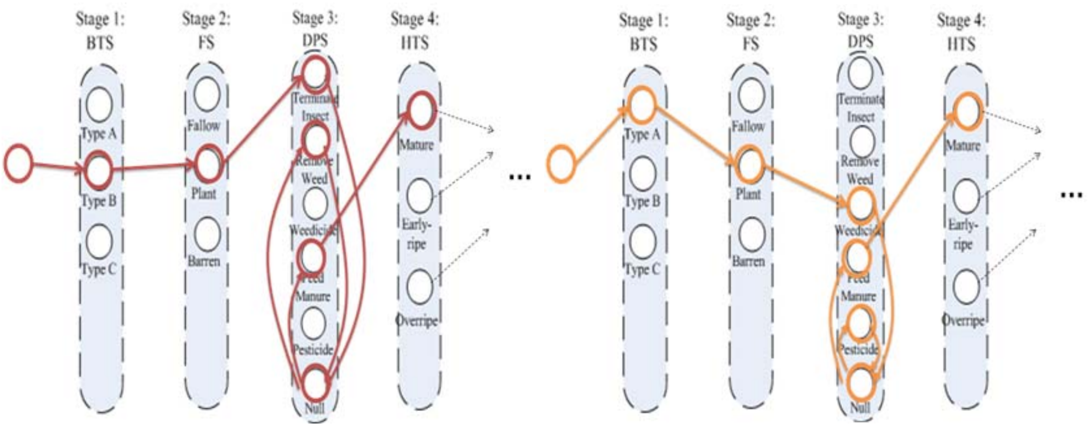


Figure 3.3 The seven stages MMG of the game "*The Banana Farm*"

Example 2. Farming scenario in the MMG model of "*The Banana Farm*"

Figures 3(a)(b) represent two different kinds of instances of farming behavior because of different thoughts in students' mind, respectively. In Figure 3(a), the collaborative team's thought is post-modern, which means the team might select banana type B in Stage 1 due to less cost and less designed disasters. Therefore, they might take "*Terminate Insect*" and "*Remove Weed*" actions to plant high quality banana in Stage 3. In Figure 3(b), their thought is small profits but quick turnover, which means they might select type A with the highest profit and the most disasters. Therefore, "*Weedicide*" and "*Pesticide*" actions might be taken in Stage 3 because of solving disasters faster. Thus, assessment can be done because different thoughts cause different sequence of decisions, which is considered as a process of scientific inquiry.



(a) Post-modern (b) Small profits but quick turnover

Figure 3.4 An example of the farming scenario design using MMG

3.2 Environment Implementation Phase

3.2.1 RPL environment frame

In the eRPL, since it is a closed environment with stereotyped objects, the property of the learning environment can be represented with attributes. Therefore, the frame knowledge representation with slots/values and event driven stored procedure is proposed to implement the environment, where four types of primitive frames for the status and action monitoring in the learning environment are presented.

- **Action frame:**

Since the student has to take actions such as sowing, harvesting etc. in Stages 1, 3 and 4, three types of frames, which are "*Banana Type Selection*" frame for selecting the soil field when sowing, "*Farming actions*" frame for taking farm actions, such as feeding, terminating insect, etc. and "*Harvesting Timing Selection*" for selecting harvesting timing are proposed.

Since the student has to take actions to select product, choose the marketing strategy and the market to sell in Stages 5, 6 and 7, two types of frames, which are "*Product Selection*" frame for selecting the product to sell and "*Market Selection*" frame for choosing the marketing strategy including taking the order of export, promoting the market, selecting the market to sell including processed market, self-market and export market.

- **Disaster frame**

The disasters such as weed-grown event or insect event may happen in Stage 3. "*Disaster*" frame with two child frames including "*Weed*" and "*Insect*" is designed.

- **Object frame:**

There are three frames for recording results of harvesting, sowing, etc.: "*Banana*", "*User status*" and "*Market status*". The "*Banana*" frame is used to record the banana status, including maturation, sweetness, type, healthiness and cost. The "*Warehouse*" frame is used to record the type together with the number of bananas. The "*Soil*" frame is used to record the soil status and planting status.

- **Status frame:**

To record the players' and markets' information, we present two frames recorded in the working memory. The first one is "*User Status*" frame, which is used for recording the user information. The second one is "*Market Status*", which is used for recording the market information.

In the staged RPL scheme, the MMG is implemented with frame representation. As shown in Figure 3.2, the designed scenario of each stage is implemented by the disaster frame to generate insect event, weed event as the testing for students. The students' actions of each stage are implemented by configuring attributes in action frames. Finally, the tracking of environmental status is implemented by the object frame and status frame.

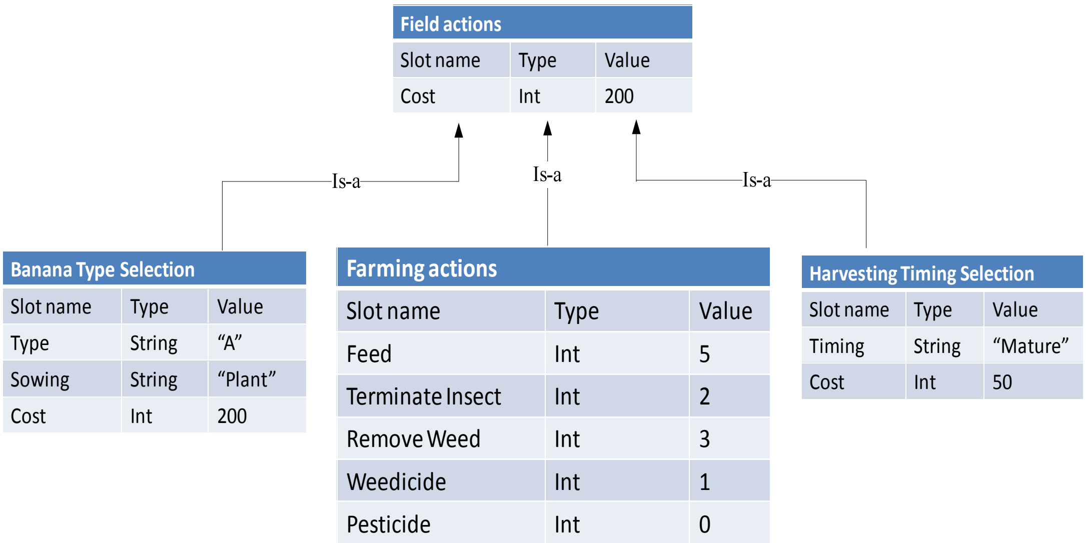


Figure 3.5 Frames for field actions

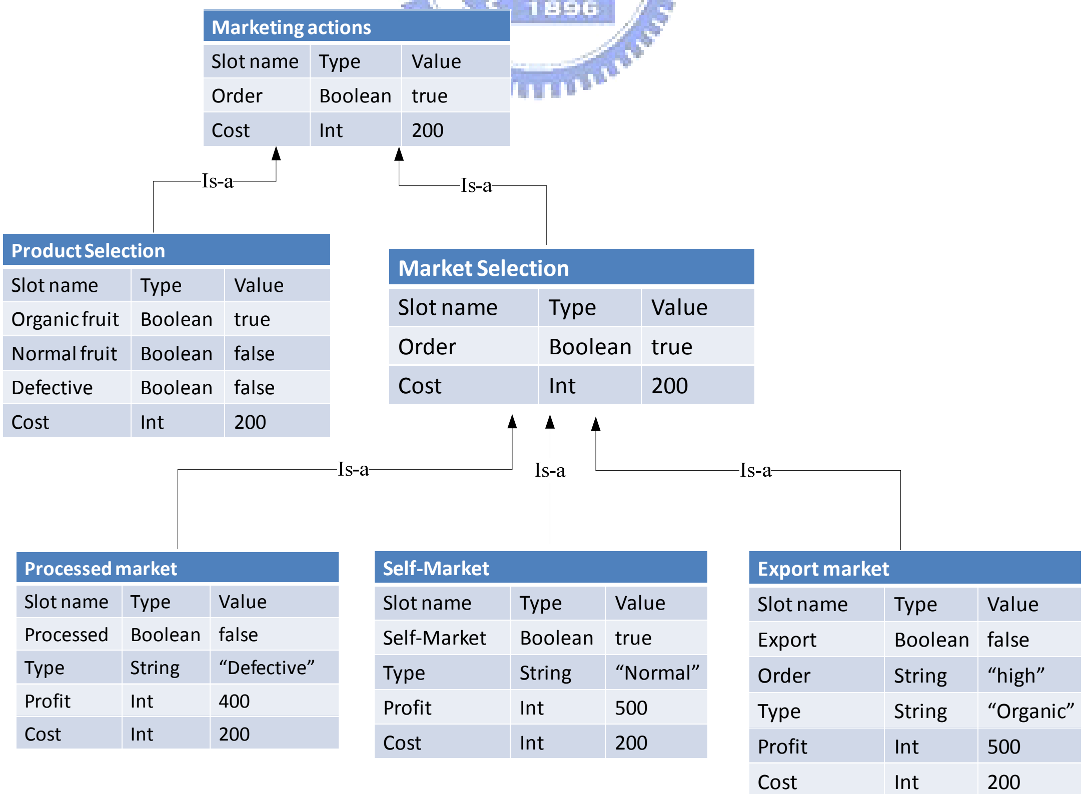


Figure 3.6 Frames for marketing actions

Disaster		
Slot name	Type	Value
Event	String	“Weed”
Value	Int	25

Is-a Is-a

Weed		
Slot name	Type	Value
Event	String	“Weed”
Value	Int	50

Insect		
Slot name	Type	Value
Event	String	“Insect”
Value	Int	60

Figure 3.7 Frames for disasters

Banana		
Slot name	Type	Name
Maturation	String	“Medium”
Sweetness	String	“High”
Type	String	“1”
Healthiness	String	“Medium”
Cost	String	“Medium”

Warehouse		
Slot name	Type	Name
Type	Int	2
Number	Int	3

Soil		
Slot name	Type	Name
Soil status	String	“High”
Planting status	String	“None”

Figure 3.8 Frames for each object

User status		
Slot name	Type	Value
Money	Int	10500
Manure	Int	400
Marathon	Int	200
Time	Int	136

Market status		
Slot name	Type	Value
Consumer Price Index	String	“High”
Market brand	Int	3
Banana type price	Int	550

Figure 3.9 Frames for each status

Example 3. The RPL environment frame of the Farming scenario

For farming scenario given in Figure 3.10, there are four stages. For example, the student chooses "*A*" in Stage 1, then select "*Plant*" or "*Null*" in Stage 2. If the "*Soil status*" slot of "*Soil*" frame is low, only the "*Plant*" action is prohibited. Only farming actions could be chosen in Stage 3. Each of farming actions has one counter used for recording the action times. Furthermore, the event such as weed-grown event or insect event may occur at this stage, such as insect event shown. The event will update the "*Healthiness*" slot of the "*Banana*" frame, causing the banana dead or unhealthy. At last, the student could harvest the banana at stage 4, where the harvest timing is important because it may affect the quality of banana.

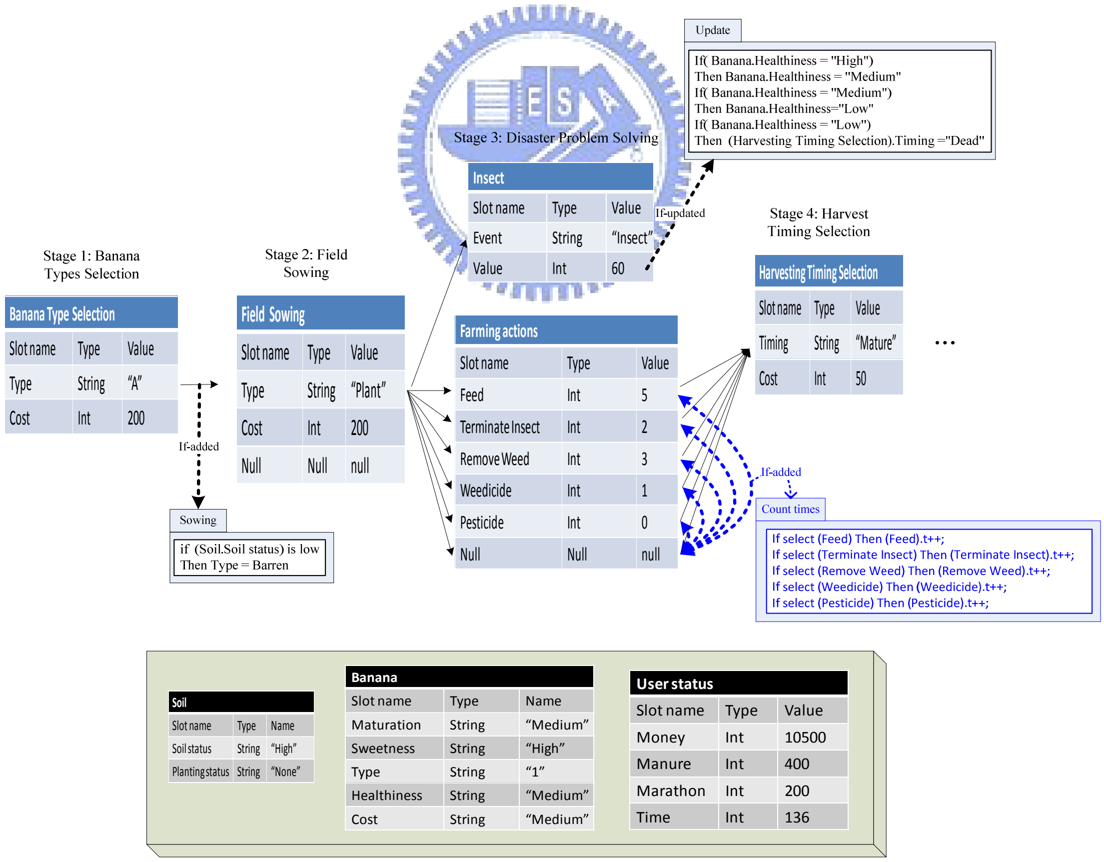


Figure 3.10 Farming scenario design using frame knowledge representation

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Chapter 4. Behavior Assessment Phase

With the e-RPL environment proposed above, the operating raw data of each student which is considered as student's behaviors was recorded in system database for assessment. For analyzing the relations of behaviors, we propose a collaborative behavior mining algorithm to discover frequent collaborative behavior patterns of the actions and interactions during the learning. Thus, with the statistical data, assessment of students' collaboration can be analyzed.

4.1 Learning Portfolio Modeling

For the analysis of students' behaviors, the e-RPL learning raw data are collected in the database using appropriate frames. Since we aim to analyze the collaboration behavior of students, the students' Collaborative Learning Portfolio is defined. In addition to learning portfolio, students' profiles such as thinking styles [20] which are acquired by questionnaire [20] are further used in this thesis for explaining students' behaviors. There are three styles, Executive (*E*) means that prefer to obey rules and deal with prefabricated questions; Legislative (*L*) means that prefer to design their own approaches to handling issues and challenges; Judicial (*J*) means that prefer to evaluate rules and deal with analytical questions. Accordingly, the team thinking style representation and the portfolio definitions are as follows.

Definition 2. Team thinking style representation

$C=(c_1, c_2)$ represents the student 1's and student 2's thinking style where $c_1, c_2 \in \{E, L, J\}$.

To simplify our discussion, assume there are k stages in this thesis, and assume there are n iterations in a play. Let an iteration denote a learning path from Stage 1 to Stage k. The transaction is defined as follows.

Definition 3. Collaborative behavior transaction $t_{ID}=(P_1, P_2)$ for the an iteration performed by team ID

- $P_1 = (p_1, p_2, \ldots, p_k)$ is a fixed length of one student's behavior path, where p_i represents the behavior obtained from the actions performed in the i-th stage.
- $P_2 = (p'_1, p'_2, \ldots, p'_k)$ is a fixed length of the other student's behavior path, where p'_i represents the behavior obtained from the actions performed in the i-th stage.

Definition 4. Collaborative Learning Portfolio L=(C, T)

- $T = \{ t_1, t_2, \ldots, t_n \}$, each t_i denotes a collaborative learning transaction.
- C denotes the team thinking style.

4.2 Collaborative Behavior Mining

The original raw data are stored into databases using appropriate frames. With the portfolio defined above, the behavior mining can be applied to discover the frequent behavior patterns of the actions and interactions during the learning. We proposed a collaborative behavior mining algorithm based upon Apriori Algorithm[19] to discover the relations of behaviors. In order to support the behavior analysis using association rule algorithm, the recorded frame values are transformed into action items with categorical data type. The algorithm is shown in Figure 4.1.

Algorithm: Collaborative Behavior Mining Algorithm

Input: e-RPL learning set D.

Minimal Support(α)

Output: The collaborative behavior association rules.

Step1. data transformation: For each d_m belongs to D

1.1 If (d_m belongs to i-th Stage without self-edge) Then

Transform dm to categorical value data.

1.2 Else If (d_m belongs to i-th Stage with self-edge) Then

- Transform actions of the i-th Stage into new actions with different accumulated action results which is represented with new items. (see example 4.1)
- Map d_m to new actions of items in this stage.

Step2. The transformed actions of all stages are integrated as the behavior paths and stored as collaborative behavior transaction.

Step3: Apply Apriori algorithm on T to discover frequent collaborative behavior association rules among the students

Step4: Output the discovered collaborative behavior association rules

Figure 4.1 Collaborative behavior mining algorithm

Example 4.1: Data transformation

For the actions of the i-th Stage without self-edge, the attribute can be directly transformed into categorical data type. For the actions of the i-th Stage with self-edge, the actions may be performed several times in one stage. For example as shown in i-th Stage in Figure 4.2, to fulfill the data format of defined collaborative behavior transaction, different accumulated actions results of "A_1", "A_2" and "A_3" can be generated and transformed to "B_1", "B_2", …, "B_8". Therefore, the original i-th Stage can be reduced to the expanded stage without original stage.

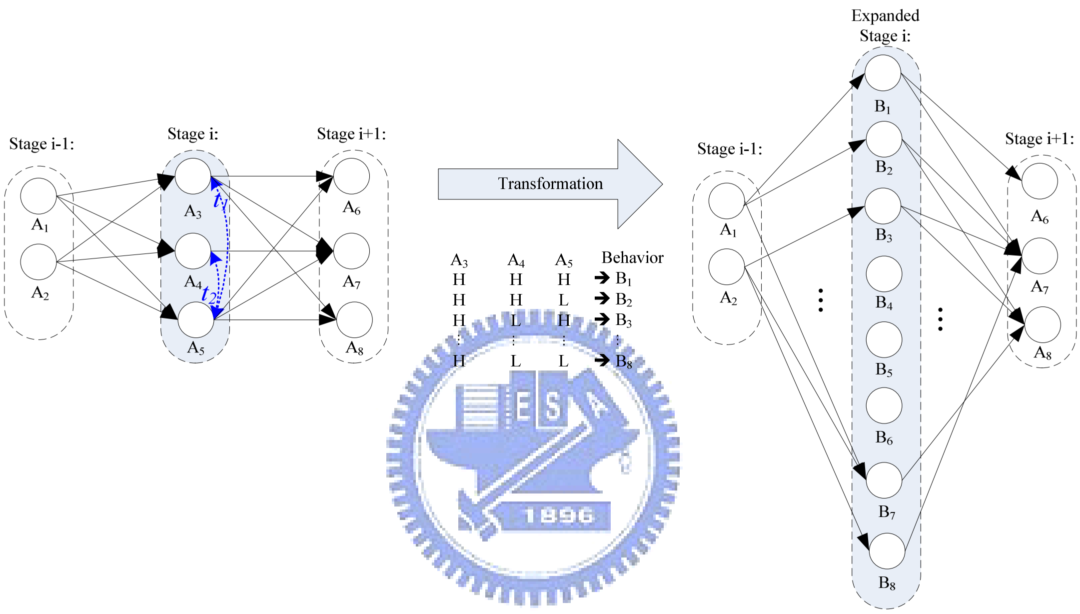

Figure 4.2 An example of data transformation

Example 4.2 Collaborative behavior pattern mining

According to the portfolio definition, an example of a team's collaborative behavior transactions is shown in Table 4.1 where three-stage scenario is used to simplify discussion. The predefined minimal support is 0.75 and the confidence is 100%. According to the collaborative behavior mining algorithm mentioned above, after executing steps 1 and 2, the data is illustrated in Table 4.1. After executing steps 3 and 4, the association rules are shown in Table 4.2.

Table 4.1 Collaborative learning transactions of the same team of two students c_1 and c_2

Transaction ID	Transactions
100	("$c_1.A_1$", "$c_1.B_3$", "$c_1.A_6$", "$c_2.A_1$", "$c_2.B_4$", "$c_2.A_7$")
200	("$c_1.A_2$", "$c_1.B_3$", "$c_1.A_8$", "$c_2.A_2$", "$c_2.B_4$", "$c_2.A_7$")
300	("$c_1.A_2$", "$c_1.B_3$", "$c_1.A_6$", "$c_2.A_2$", "$c_2.B_5$", "$c_2.A_7$")
400	("$c_1.A_2$", "$c_1.B_4$", "$c_1.A_6$", "$c_2.A_1$", "$c_2.B_3$", "$c_2.A_7$")

Table 4.2 Association rules for the same team of two students c_1 and c_2.

Association rules (sup = 0.75, conf = 100%)
("$c_1.A_2$", "$c_2.A_7$")
("$c_1.A_6$", "$c_2.A_7$")
("$c_1.B_3$", "$c_2.A_7$")

Chapter 5. Experiment Design and Findings

5.1 Experiment Design

In this experiment, there are 47 teams from junior high school students participated the learning activity on "*The Banana Farm*". Each student may join more than one team at different time. Same teams may have similar characteristic and others have different characteristics. Thus, 47 groups are divided based upon four characteristics shown in Table 5.1.

Table 5.1 Number of teams in four characteristics

Team member style	Number of teams
Team with *Executive* and *Judicial*: (*E, J*)	11
Team with *Executive* and *Executive*: (*E, E*)	11
Team with *Legislative* and *Executive*: (*L , E*)	19
Team with *Legislative* and *Legislative*: (*L, L*)	6

5.2 Findings of students' collaborations

To explain the findings, we refer to three tables. Table 5.2 shows explanations of each attribute and related stages in Table 5.3 and Table 5.4. Table 5.3 shows the statistical results of planting and marketing for designed scenario mentioned in Section 3.1.1. Table 5.4 shows drill down results from Table 5.3 for analyzing each team member.

Table 5.2 Explanation of each attribute in Table 5.3 and Table 5.4

Column name	Explanation	Stage
Avg. survival rate (*ASR*):	Total number of planted banana / total sowed banana number	Stages 3, 4
Avg. harvesting banana (*AHB*)	Total number of harvested banana / total team number	Stage 4
Avg. high quality rate for harvesting (*AHQRH*)	Total high quality of harvested banana number / total harvested banana number	Stage 4
Avg. total sold banana (*ATSB*)	Total number of sold banana to market / total team number	Stage 7
Avg. high quality rate for selling (*AHQRS*)	Total high quality of sold banana number / Total sold banana	Stage 5
Avg. market brand (*AMB*)	Self-market brand / total team number, Export market brand / total team number, Processed market brand / total team number	Stage 7
Avg. learning result (ALR)	Rank of (total money / total team number)	Working memory
Avg. survival rate for each member (*ASRM*)	Total number of planted banana / total sowed banana number for the first/second team member	Stages 3, 4
Avg. high quality rate for harvesting for each team member (*AHQRHM*):	Total high quality of harvested banana number / total harvested banana number for the first/second team member	Stage 4
Avg. high quality rate for selling for each team member (*AHQRSM*)	Total high quality of sold banana number / Total sold banana for the first/second team member	Stage 5

Table 5.3 Statistical results of different type of team's portfolio

Team member style	Avg. survival rate (ASR)	Avg. harvesting banana (AHB)	Avg. high quality rate for harvesting (AHQRH)	Avg. sold banana (ASB)	Avg. high quality rate for selling (AHQRS)	Avg. market brand (AMB)	Learning result (ALR)
Team with *E* and *J*: (*E*, *J*)	77.6%	34.6	71.4%	21.5	90.6%	(16.5, 102, 1.9)	2
Team with *E* and *E*: (*E*, *E*)	78.8%	36.9	65.5%	27	88.6%	(1.3, 115.2,10.2)	1
Team with *L* and *E*: (*L*, *E*)	71.7%	31.8	57%	20.36	77.2%	(48, 71.5, 7.95)	4
Team with *L* and *L*: (*L*, *L*)	84.8%	32.3	71.1%	23.5	87.2%	(2.3, 123.7,11.7)	3

Table 5.4 Statistical results of each type of teams' members' portfolio

Team member style (Each team member)		Avg. survival rate for each team member (ASRM)	Avg. high quality rate for harvesting for each team member (AHQRHM)	Avg. high quality rate for selling for each team member (AHQRSM)
Team with *E* and *J*: (*E*, *J*)	Executive	67%	58%	90.7%
	Judicial	90%	83.5%	90.6%
Team with *E* and *E*: (*E*, *E*)	Executive	70.7%	49.7%	90.8%
	Executive	87%	78.2%	87.6%
Team with *L* and *E*: (*L*, *E*)	Legislative	67.8%	57.1%	79.4%
	Executive	73%	56.8%	75.2%
Team with *L* and *L*: (*L*, *L*)	Legislative	89.7%	79%	84.6%
	Legislative	79.5%	61.7%	93%

For analyzing each type of team further, the collaborative behavior patterns are evaluated.

Table 5.5 Collaborative behavior patterns for team with Executive students c_1 and Judicial students c_2

Patterns(Minimum support: 0.28)	**Explanations**
(1) c_1: fail planting, c_2: feeding banana (59%) (2) c_1: fail planting, c_2: harvesting organic banana (45%)	Most of Executive students always fail planting when most of Judicial students feeding banana or harvesting organic banana.
(3) c_1: feeding banana, c_2:harvesting organic banana (56%) (4) c_1:feeding banana, c_2: selling banana to export market (33%)	Work collaboratively for feeding banana, harvesting organic banana and selling banana to export market.

- **Collaboration result: Judicial student dominate the team.**

According to the results of Table 5.3 and Table 5.4, average team's learning result is relatively high. In the Stages of farming scenario, although teams got low survival rate, they not only harvested high number of bananas, but also got the highest quality rate for harvesting. It seems that they tradeoff well between quantity and quality. In the Stages of marketing scenario, they not only got the highest rate for selling but also sold bananas to the export market for increasing market brand which means they understand the importance of the market brand. In sum, they got good learning result in average. For further analyzing teammates' behaviors, most of Executive students got low survival rate but high quality of banana. Most of Judicial students harvested large number of high quality banana and sold them by export market. In addition, with the discovered association rules shown in Table 5.5, we may conclude that Judicial student dominate the team and work collaboratively for feeding banana, harvesting organic banana and selling banana to export market.

Table 5.6 Collaborative behavior patterns for team with both Executive students c_1, c_2

Patterns: (Minimum support: 0.25)	**Explanations**
(1) c_1: feeding banana, c_2: harvesting organic banana (25%) (2) c_2: harvesting banana, c_1: feeding banana (25%)	Both of the students were harvesting organic banana collaboratively
(3) c_1: selecting organic banana, c_1: selling to export market (39%) (4) c_2: selecting organic banana, c_2: selling to export market (32%)	Both of the students were selecting organic banana and selling to export market.

- **Collaboration result: Two executive students work with well collaboration to achieve good result.**

  According to the statistic results of Table 5.3 and Table 5.4, these teams go highest learning result. In the Stages of farming scenario, they harvested the most number of bananas and got high quality rate of banana. It seems that they tradeoff well between quantity and quality. In the Stages of marketing scenario, they sell high quality rate of banana and got high market brand value. By detailedly observing teammates' behaviors, only one of the Executive students got high quality rate of harvested banana. In Table 5.6, we find out that they both planted organic bananas and sold them to export market. Therefore, we may conclude that two Executive students work with well collaboration to achieve good result and they mainly focus on organic banana planting.

Table 5.7 Collaborative behavior patterns for team with the Legislative student c_1 and the Executive student c_2

Patterns: (Minimum support: 0.25)	Explanations
(1) c_1: feeding banana, c_2: harvesting organic banana (42%) (2)c_1: harvesting organic banana, c_2:feeding banana (63%)	Both of students were harvesting organic banana and feeding banana together.
(3) c_1: feeding banana, c_2: selling to export market (35%) (4) c_2: feeding banana, c_1: selling to export market (30%)	Both of the students were feeding banana and selling banana export market together.
(5) c_1: fail planting, c_2: feeding banana (48.5%) (6) c_1: feeding banana, c_2: fail planting (39%)	Both of the students were feeding banana and planting fail at the same time.

- **Collaboration result: Legislative student and Executive student work together but fail a lot.**

  According to the statistic results of Table 5.3 and Table 5.4, these teams got lowest learning result. In the Stages of farming scenario, they only harvested a small number of bananas and got the lowest survival rate. It seems that they did not tradeoff well between quantity and quality. Consequently, in the Stages of marketing scenario, they got low market brand value. However, for further analyzing teammates' behaviors as shown in Table 5.7, we find out that most of teams fed, harvested and sold to export market at the same time. We may conclude that Legislative student and Executive student work together but fail a lot.

Table 5.8 Collaborative behavior patterns for both Legislative students c_1, c_2

Patterns: (Minimum support: 0.35)	**Explanations**
(1) c_1: harvesting organic banana, c_2: feeding banana (63%) (2) c_1: feeding banana, c_2: harvesting organic banana (42%)	Both of the students harvesting organic banana and feeding banana together.
(3) c_1: feeding banana, c_2: feeding banana (84%)	Both of the students were feeding banana at the same time.

- **Collaboration result: One of Legislative students as leader and the other as assistant.**

According to the statistic results of Table 5.3 and Table 5.4, these teams got good learning result. In the Stages farming scenario, they got the very high survival rate. It means they are very good at planting. In the Stages of marketing scenario, they got high selling rate for banana and got the highest market brand value. For further analyzing teammates' behaviors as shown in Table 5.8, we find out that one of Legislative students focus on planting and harvesting. We may conclude that one of Legislative students as leader and the other as assistant and they take most of time on the quality of planting.

Chapter 6. Conclusion & Future Work

In this thesis, we propose a Staged RPL Scheme (SRS) which is used for making assessment including problem solving and scientific inquiry in Scientific Literacy education domain by means of role-playing learning. Prior research dealing with role-playing game did not explore the idea of assessment design. Therefore, we mainly concerned the issues of how to discover and analyze the behaviors or intentions of the students from the portfolio and how to discover the causal relations of behaviors become two important issues. The SRS includes three phases, the Modified Multi-stage Graph (MMG) model for learning design, frame knowledge representation for environmental implementation, and a collaborative behavior mining algorithm for discovering the collaborative behavior of the team.

The findings and results show that there are four different types of collaborative behavior patterns, including “one of the teammates dominates”, “two teammates work with well collaboration to achieve good result”, “two students work together but fail a lot” and “one of the teammates as a leader and the other as assistant”. It is beneficial for teachers to analyze student’s learning performance.

In the near future, we will extend the MMG model to support assessment for advanced knowledge such as strategic learning with dynamic stages and decisions.

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