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เอเจนต์สำหรับแยกประเภทของบทบาทในทีมการเรียนรู้ร่วมกัน

AN AGENT FOR ROLES CLASSIFICATION OF A COLLABORATIVE LEARNING TEAM

โดย

ดร. พรรณฤมล เต็มดี

สำนักวิชาเทคโนโลยีสารสนเทศ

งานวิจัยนี้ได้รับทุนสนับสนุนจากมหาวิทยาลัยแม่ฟ้าหลวง

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EXEXCUTIVE SUMMARY

Introduction

As the same time that education system is shifting from traditional classroom to the virtual classroom on VLE, collaborative learning is drawing increasing interest because of the belief that it is an effective pedagogical approach for modern education. Collaborative learning is defined as a learning process that emphasizes group or cooperative efforts among instructors and students. Once collaborative learning is applied to VLE, the supporting pedagogical facilities including collaborative activities and communication tools are discovered and developed for promoting this kind of learning. The instructor's role is changed from knowledge provider to facilitator. This has the implications for the amount of technical support that may be required.

Unlike those in the traditional classroom, the collaboration of students through the collaborative learning environment needs more attention from the instructor because of the difficulty of getting feedback from online students. From face to face interaction, the instructor is able to observe students' actions immediately but not from the online collaboration. Moreover, the instructor needs to keep track of all collaborations so that he or she would be able to control group/class situation in time. Unfortunately, he or she can not actively participate in all activities; therefore someone who will be able to voluntarily perform this time and effort consuming task is needed. Using software agent seems to be the most appropriate fulfilment; therefore the study of the instructor assistant agent is proposed here.

Objective

An instructional assistant agent developed in this research is assigned to take the role of monitoring the collaboration and classifying the leaders of a collaborative learning team in VLE.

Computational theory

This research employs three theories including social network analysis, software agent and neural network. The details of those theories are explained in Chapter 3 later on.

Social Network Analysis

Social Network Analysis pays attention to the properties of the whole network not only for the individual's attributes. Social network data are formalized either ways of three major mathematical foundations of network methods including graph theory, statistical and probability theory and algebraic models. Gathering social network data involves both observation and recording of activities.

The individuals having the highest degree of centrality are likely to have the most expert power in the team. Closeness reveals how close the individual to other team members. The individuals having highest closeness will be able to reach all (most) team members quickly when necessary. Finally, Betweenness reveals how often the individuals being in between several paths of pairs of actors. It implies how much the influence of these individuals to the ongoing collaborations. In conclusion, the leaders should occupy all characteristics mentioned before. This research believes that the leadership is evolved over the collaboration time. Therefore, this research aims to study the patterns of those three measurements so that the research question can be answered. The research question of this research is whether the patterns of those three measurements are able to classify the leader according to the leadership perceptions of team members.

Software Agent

This research implements the agent for monitoring and classifying the leader from the pattern classification of three social network measurements.

Neural Network Analysis

Artificial neural network is a mathematical processing of information by using connectionist model as in the biological nervous system. A neural network is known as a parallel distributed processing network. This research uses neural network to classify the similarity of the patterns for all three social network measurements.

Research methodology

This research consists of 3 main parts including obtaining the leadership perception from the real experiment with teams of students, classifying the leader according the leadership perception by using neural network, and agent implementation. The details of those steps are explained below.

Pilot Study

The pilot studies are conducted to study how students percept the leadership from team members. The students are grouped in team with 5 persons per each. The students in the team have no teamwork experience before. They are assigned to work together in FLE only through the discussion board. At the end of the collaboration time, all students are asked who the leader is. They can name more than one leader. By the time the collaboration goes on, the agent keeps recording three social network measurements.

Leader Classification by Neural Network

After having the leader classified by using Social Network Analysis, the interaction patterns are again classified by neural network. This research uses the backpropagation neural network having 3 layers, 10 input units, 2 hidden units and 1output unit as a classifier. The patterns of social network measurements of all teams are used for training and testing.

Agent Implementation

This research implements the agent in JADE (Java Agent Development Framework). This research implements the user interface to the user by showing the collaboration pattern, showing the patterns of all measurements and showing the name of the leader.

Results and Discussion

The results show that the pattern of degree of centrality can distinguish between the leadership of members more effective than patterns of closeness and betweenness. It can be shown from the patterns of closeness and betweenness that they are not varying prominently enough for distinguish between the roles of team members. There is also the case that there is the voted leader while there is no classified leader. There might be the bias of team members, which they already know who the leader is even that member does not perform well enough to be a leader according to the trained patterns. Besides the evolution of the pattern, the values of the measurements are also used to train the neural network.

In conclusion, the neural network based agent can effectively classify the leader according to the leadership perception of team members. After testing with 27 testing patterns the classification accuracies are 94.4 % from pattern of degree of centrality patterns, 64.7 % from closeness pattern, and 70.6 % from betweenness patterns.

Conclusion

This research proposes the instructional assistant agent performing as the neural network based classifier to monitor the collaboration and identify the leader from team members of a collaborative learning team. The results show that the proposed agent is able to classify the leader according to the leadership perception with 94.4% from degree of centrality patterns, 64.7% from closeness patterns, and 70.6% from betweenness pattern.

เอเจนต์สำหรับแยกประเภทของบทบาทในทีมการเรียนรู้ร่วมกัน

บทคัดย่อ

ในปัจจุบันสิ่งแวดล้อมการเรียนแบบเสมือนได้มีบทบาทสำคัญมากต่อระบบการศึกษารูปแบบใหม่ โดยเฉพาะบทบาทในการพัฒนากระบวนการการเรียนรู้ งานวิจัยชิ้นนี้นำเสนอเครื่องมือเพื่อช่วยสนับสนุนกระบวนการการเรียนรู้ในสิ่งแวดล้อมการเรียนแบบเสมือน โดยการสร้างเอเจนต์สำหรับการแยกประเภทของบทบาทในทีมการเรียนรู้ร่วมกัน ค่าของการวิเคราะห์เครือข่ายสังคมต่างๆ ได้แก่ค่า ดีกรีของการเป็นศูนย์กลาง โคลสเหนส และบีทวีนเหนส ถูกนำมาใช้สำหรับการแยกผู้นำออกจากผู้ติดตามของการเรียนรู้ร่วมกัน โครงข่ายประสาทเทียมแบบแบล็กพรอบพาเกชั่นถูกนำมาใช้เป็นตัวแยกบทบาทต่างๆในทีม จากการทดลองกับทีมนักศึกษาสิบทีม ทีมละ 5 คนพบว่าเอเจนต์ที่นำเสนอให้ความถูกต้อง 94.4%, 64.7% และ 70.6% จากข้อมูลของค่าดีกรีการเป็นศูนย์กลาง จากข้อมูลของโคลสเหนส จากข้อมูลของบีทวีนเหนสตามลำดับ

คำสำคัญ: เอเจ้นท์, การแยกประเภทของบทบาท, การวิเคราะห์เครือข่ายสังคม, โครงข่ายประสาทเทียม

AN AGENT FOR ROLES CLASSIFICATION OF A COLLABORATIVE LEARNING TEAM

ABSTRACT

Nowadays, a virtual learning environment (VLE) has been playing an important role for new education particularly for enhancing the learning process. This research proposes the tool for help supporting the learning process in VLE. More specifically, this research develops an agent for classifying leaders and followers in a collaborative learning team. The measurements of social network analysis are studied and used for role classification including degree of centrality, closeness and betweenness. Backpropagation Neural Network is used as a classifier. For the classification accuracy, the results with ten teams of students and five persons per each show that the proposed agent provides 94.4%, 64.7% and 70.6% from the pattern of degree of centrality, closeness and betweeness respectively.

Keywords: Agent, Role Classification, Social Network Analysis, Neural Network

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FIGURE CONTENT

CHAPTER 1

INTRODUCTION

1.1 Background

For years, collaborative learning (Hiltz, 1988) has been announcing as a promising learning instruction for enhancing individuals' cognitions through the social interaction of the small team. However, collaborative learning is not just simply arranging students to work in team. The underlying premise of collaborative learning is the consensus built through the collaboration of team members without the competition.

Once collaborative learning concept is applied to online learning, the amount of technical support is, thus, required to promote the instruction and to overcome the difficulties distracting the effective collaboration in the virtual learning environment. Consequently, the concept of computer supported collaborative learning (CSCL) has emerged to provide the technology support along side the migration of collaborative learning and the requirements of the instructor and the online students.

Due to the asynchronization mode of the collaboration, which online students will be able to collaborate among each other anywhere and anytime, much effort from the instructor is required to provide the real time facilitation to the team especially when there are many teams at the same time. Consequently, this research, which is the

CSCL research study, proposes a software agent assisting the instructor to facilitate the class as the same manner as the actual instructor for specific functions which are real time monitoring and role classifying.

Generally, the online students in a collaborative learning team perform variety kinds of roles during their collaboration. Moreover, those roles are interchangeable. The ability to better understand the role performing during the learning process of a collaborative learning team is very crucial, in order to effectively support online students. Those benefits are for example, providing an effectively support for online students to enhance group performance (Singley et al., 1999; Ou et al., 2005; Chen et al., 2002), providing the strategy for designing the activities to practice the social skill required for role allocation and developing the virtual role based environment (Dafoulas and Macaulay, 2001; Slator et al., 2001), etc.

This research aims to study and develop the model for classifying the role performed by online students in a collaborative learning team. The interested roles are the leader, and the follower. Role performing is important because not only they can be used further as the key identifying the potential of team performance [Ou et al., 2005], but also for the key assessing the individual development of each individual in the team. Finally, the discovered model will be implemented in a software agent, which will be assigned to assist the real instructor to perform the role classification automatically.

1.2 Objective

This research has two main objectives including:

1. Studying and developing the effective model for classifying the leader and the follower in a collaborative learning team.

2. Developing an intelligent software agent to perform the classification task regarding to the discovered classification model.

1.3 Output

The output of this research is the software agent implementing the model for classifying the leader and the follower. Not only will this agent be able to assist the instructor providing the real time monitoring to the collaborative learning team, but also this agent would be adapted later for any other specific model for any particular tasks of online learning.

1.4Computational Theory

This research employs three theories including social network analysis, software agent and neural network. The details of those theories are explained below.

1.4.1 Social Network Analysis

Social Network Analysis (Wasserman and Faust, 1999) pays attention to the properties of the whole network not only for the individual's attributes. Social network data are formalized either ways of three major mathematical foundations of network methods including graph theory, statistical and probability theory and algebraic models. Gathering social network data involves both observation and recording of activities.

1.4.2 Software Agent

This research implements the agent for monitoring and classifying the leader from the pattern classification of three social network measurements. Figure 1-1 shows the concept of implementing the agent in this research.

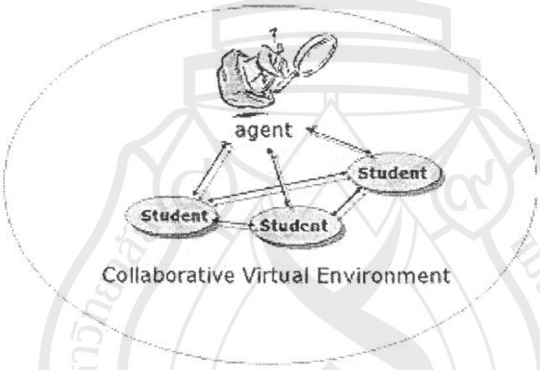

Figure 1-1 Agent Architecture

1.4.3 Artificial Neural Network

Artificial neural network is a mathematical processing of information by using connectionist model as in the biological nervous system. A neural network is known as a parallel distributed processing network. This research uses neural network to classify the similarity of the patterns for all three social network measurements.

1.5 Research Question

The knowledge in a collaborative learning team is constructed socially. Therefore the collaboration among team members is mainly investigated in this proposal to extract the particular pattern that can be used to classify role performing of those members. The principle concept of Social Network Analysis, SNA, is thus applied here to describes the characteristics of collaboration in the term of social network data. The main assumption for this proposal is that online students normally act differently to any other team members. Therefore, different types of role should have different collaboration patterns. Alternatively, different roles should have different social network pattern. However, the students normally adapt their roles over the collaboration time. Consequently, the concept of pattern recognition is applied to capture those changing social network data. Finally, the new technique for classifying those dynamic social network data will be developed and implemented in the software agent.

The individuals having the highest degree of centrality are likely to have the most expert power in the team. Closeness reveals how close the individual to other team members. The individuals having highest closeness will be able to reach all (most) team members quickly when necessary. Finally, Betweenness reveals how often the individuals being in between several paths of pairs of actors. It implies how much the influence of these individuals to the ongoing collaborations In conclusion; the leaders should occupy all characteristics mentioned before. This research believes that the leadership is evolved over the collaboration time. Therefore, this research aims to study the patterns of those three measurements so that the research question can be answered. The research question of this research is whether the patterns of those three measurements are able to classify the leader according to the leadership perceptions of team members.

1.6 Scope

For this research, the experiment with online learning session will be conducted on the open source learning platform named Future Learning Environment or FLE (Leinonen, 2002). The online students will be grouped in a team (5 persons per team) in order to achieve the assigned questions together. All teams of online students are organized according to the different topics. However, this research mainly studies the team members who have no experience in teamwork and the topic before.

1.7 Terminology

Collaborative Learning, Role Classification, Computer Supported Collaborative Learning (CSCL), Intelligent Software Agent, Social Network Analysis (SNA), Pattern Recognition

CHAPTER 2

LITERRATURE REVIEW

2.1 Related Works

In this session, the related works of this research are briefly explained following:

2.1.1 Software Agent

The software agent is programmed to solve alternative problems. The learning may proceed and the decision is made to respond the environment. Software agent may form multi agent system which developed from Distributed Artificial intelligent (DAI), Distributed Problem Solving (DPS) and Parallel AI (PAI). An early research works, Carl Hewittis (Hewittis, 1997) proposed a concept of the agent, which is "A self-contained, interactive and concurrently-executing object, possessing internal state and communication capability" in 1997. In 1988, Bond, Gasser and Huhns (Gasser et al., 1988) proposed work concentrating on macro issue for example the interaction and the communication between agents, the decomposition and the distribution of tasks, the coordination and the cooperation, the conflict resolution via negotiation, etc. Wooldridge and Jennings (Wooldridge et al., 1995) used the macro issue for the development of the architecture and the language issue. Since 1990, software agents continuously evolve and have diversification types (Wooldridge et al., 1995).

2.1.2 Artificial Neural Network

Artificial Neural Network (ANN) is used to classify patterns and detect the notice by human. Neural network can train until become an expert by providing the situation of interest and answers. Neural network can learn how to do tasks based on the given training data or initialing experience. In 1972, Henry Klopf developed a basic for learning in artificial neurons called heterostasis. Until 1974 Paul Webos developed and used back-propagation learning method. In 1988, Grossberg and Gail Carpenter explored the Adaptive Resonance Theory (ART). ART is algorithm that represents a class of neural network architectures which is an unsupervised learning model. After that, neural network is popularized and widely proposed to many research works today.

2.1.3 Social Network Analysis

Before expressing in more details how SNA is adapted in this research, it is necessary to illustrate the research areas applying SNA. Much research employs the prominent feature of SNA, which is the ability to capture the inner structures of the network and describes those structures with the simple measurements for the structure and the individual analysis. SNA has become popular since it was being applied as a methodology for analyzing the interaction processes in the groupware environment, which is the specific area of Computer Supported Cooperative Work (CSCW). It is particularly used for determining and understanding how people work together. Many studies examined how work behaviors change when the participants are supported by different kinds of media (Eveland and Bikson, 1988; Qureshi, 1995; Yao and

McEvily, 2000; Zack, 2000; Johnston and Linton, 2000). Additionally, because of the common interest between CSCW and CSCL, there have been the exiting attempts using SNA for understanding the behavior of the online students in a collaborative learning environment, which is influenced by different supporting materials (Haythornthwaite and Wellman, 1998; Haythornthwaite, 1999; Gravelin et al., 2000). Those studies shared the attempts to understand how the media affect the relationship between people and clarify what leads people to use one medium rather than others. This finding affected the design and the development of the appearance of the virtual learning environment and the communication tools for distributed worker/learner to overcome all kinds of constraints including time, space and social aspect.

Even though the current studies still employ SNA as a power tool for revealing the inner structure of the network, the objective of employing SNA has been changing. Instead of paying attention to understanding under what environments team members will be able to collaborate successfully, the recent studies have been focusing on how the inner factors in the team would enhance team performance. Many of these studies used the structural properties of SNA to discover the relationship between many factors with the team performance. The example of those factors are the team structure (Ortiz et al., 2004; Cummings and Cross, 2003; Yang and Tang, 2004), and the communication style (Cho et al., 2005), etc. Alternatively, many of current studies employed the individual network position, to discover how the individuals' network positions affect team performance (Smith-Doerr et al., 2004) and how the individuals obtained those network positions in the network (Klein et al., 2004; Cross et al., 2001; Casciaro, 1998).

2.2 Computational Theory

Three main computational theories used in this research including software agent, social network analysis and neural network are described as following:

2.2.1 Software Agent

An agent is anything that viewed as perceive (Hyacinth S. Nwana, 1996) its environment thought sensors and acts upon that environment thought actuator which shows in Figure 2-1. The definitions from Cambridge dictionary that agent is "a person who acts for or represents another". Later the properties of agenthood were also defined (Hyacinth S. Nwana, 1996) that any software entities exhibiting these features are considered as agent:

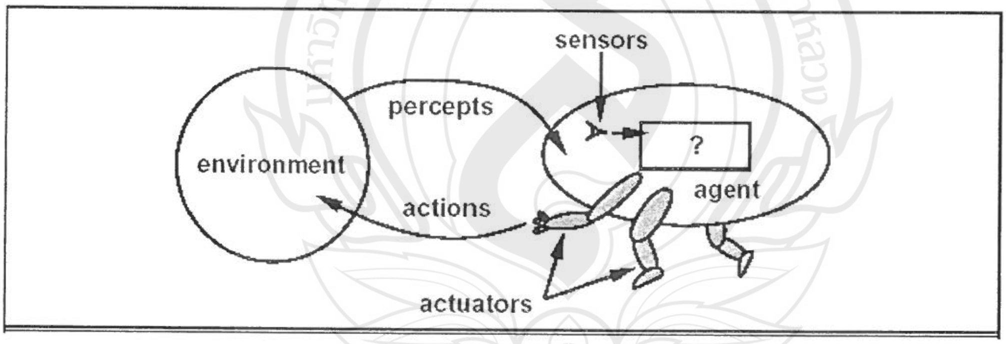

Figure 2-1 An Agent Interacting with Environment (Russell, S. and Norvig, P., 2003)

Learning Ability

Agent learned by receiving the event from the environment and processes to make decisions. It can get knowledge by itself and inference engine. Following the black box concept, an agent percepts the event, it will collect an action to response to environment. Finally agents become expert system.

Agent Platform

The Agent Platform is the set of active containers which include main container and normal containers. FIPA define the model standard of an agent platform in Figure 2-2

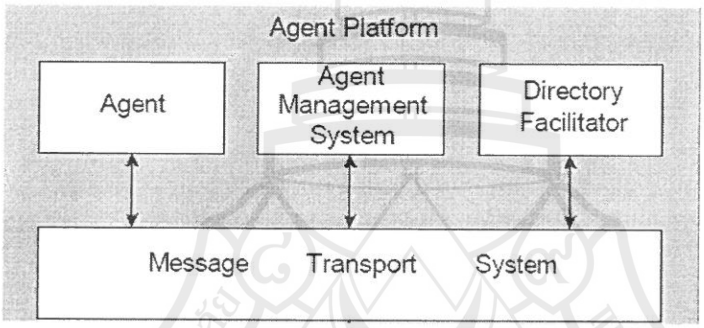

Figure 2-2 Architecture of a FIPA Agent Platform

The Agent Management System (AMS) is the agent's supervisor working control over access to and use of the agent platform. The single platform requires only one AMS, it preparing white-page and life-cycle service, maintaining a directory of agent identifiers (AID) and agent state (Jennings et al., 1996). Every agent need to register with an AMS in order to a get valid AID. The Directory Facilitator (DF) is the agent who provides the default yellow page service in the platform. The Message Transport System is called Agent Communication Channel (ACC). It is a software component controlling all the transfer of message into the platform, including message to remote platforms. Figure 2.3 shows the architecture of agent platform, when JADE platform is launched, the AMS and DF are quickly produced and the ASS module is set to allow message communication. The agent platform will split the host, which is executed only one Java application, and only one Java Virtual Machine (JVM). Each JVM is conclude a basic container of agent that provides a complete run time environment but the main container agent is the live of AMS and DF and RMI registry is used internally by JADE.

2.2.2 Artificial Neural Network

Artificial neural network or neural network (Fausett, L., 1994) is a mathematical processing of information by using connectionist model for example biological nervous system in Figure 2-3. Each network is a simple processor, each possibly having a small amount of local memory. The units are connected by unidirectional communication connections which carry numeric as opposed to symbolic data (Van Nostrand., 1993). A neural network is known as a parallel distributed processing network. It is a computing solution that is loosely modeled after cortical structures of the brain.

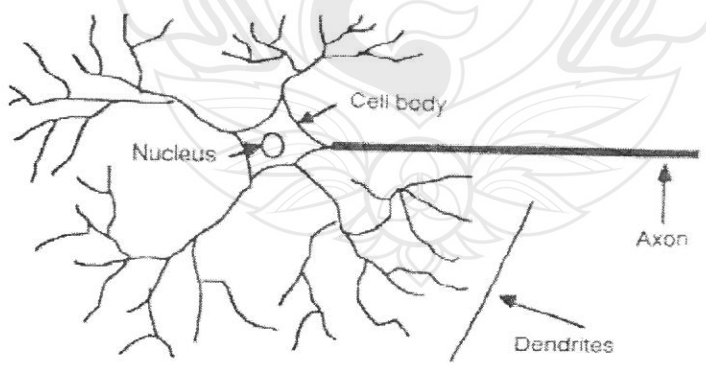

Figure 2-3 Model of Neuron in Human Brain (Fausett, L., 1994)

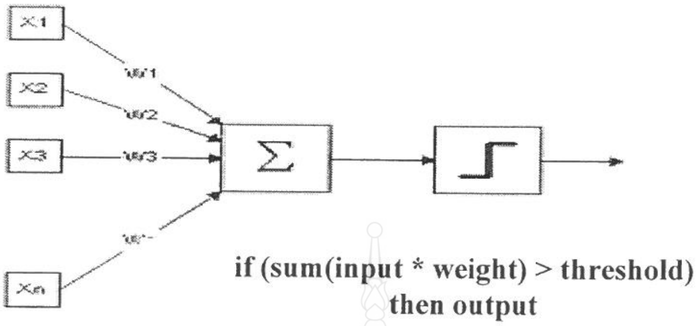

Figure 2-4 Function of neural network

Figure 2-4 shows the function of neural network that works if sum of input multiplied with weight more than threshold, there is the output. If sum of input multiplied with weight less than threshold, there is no output.

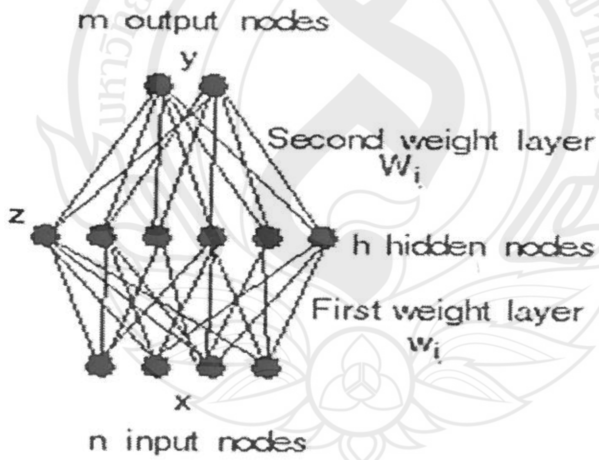

Figure 2-5 Architecture of multilayer network

Figure 2-5 shows the architecture of multilayer network consisting of input nodes, output nodes and hidden nodes. The nodes are interconnected processing elements or neurons that work together to produce an output function. The output of a neural network relies on the cooperation of the individual neurons within the network to operate. Processing of information by neural networks is characteristically done in parallel rather than series as in earlier binary computers or Von Neumann machines (Van Nostrand., 1993).

Back-propagation Algorithm

Back-propagation is a learning algorithm technique used for training multilayer perceptron as shown in Figure 2-6. Back-propagation is appropriate for the weight which connected between nodes. Several weights depend on the difference of output which needs separated computation.

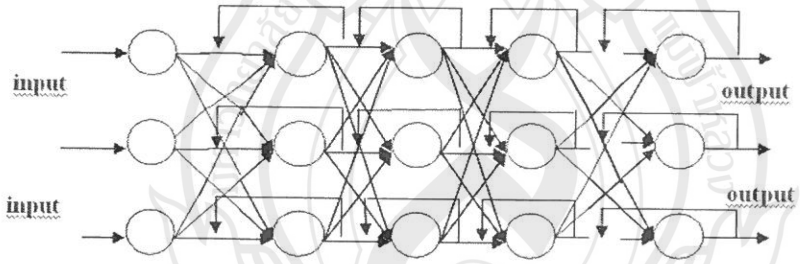

Figure 2-6 Back-propagation neural network model

This research chooses Back-propagation algorithm for training neural network because it is appropriate for training multilayer perceptron. Back-propagation neural network gets knowledge by learning the reasonable of cause. It is more complicate and harder than simple layer network. Moreover if it has been trained appropriately, it will be able to make decision effectively.

The main steps of training on a pattern for back-propagation neural network

Step 1: Present the pattern at the input layer

Step 2: Let the hidden units evaluate their output using the pattern n

$$net_j = \sum_{r=1}^{n} W_{ri} X_r \text{ and } Z_i = f_1(net_j) \tag{2.1}$$

Where: net_j = the weighted sum of inputs for unit j

W_{ri} = weight on X_r

Xr = r^{th} input to i unit

$Z_i = \dfrac{1}{1+\exp(-net_j)}$

Step 3: Let the output units evaluate their output using the result in step 2 from the hidden units.

$$net_j = \sum_{i=1}^{h} W_{ij} Z_j \text{ and } y_j = f_2(net_j) \tag{2.2}$$

Where: net_j = the weighted sum of inputs for unit j

W_{ij} = weight of input i, output j

$y_j = \dfrac{1}{1+\exp(-net_j)}$

These steps are known as the forward pass

Step 4: Apply the target pattern to the output layer

Step 5: Calculate on the output nodes

$$\delta^j = \sigma'(a^j)(t^j - y^j) \tag{2.3}$$

Where: δ^j = output node

$\sigma'(a^j)$ = the error of node j

$(t^j - y^j)$ = the difference of slope

Step 6: Main each output node using gradient descent

$$\Delta w_i^j = \alpha\delta^j x_i \tag{2.4}$$

Where: Δw_i^j = weight change between i and j

α = learning rate

x_i = input vector i

Step 7: For each hidden node, calculate according to

$$\delta^k = \sigma'(a^k)\sum_{j \in Ik}\delta^j w_k^j \tag{2.5}$$

Where: δ^k = hidden of node k

$\sigma'(a^k)$ = error of node k

w_k^j = weight of input i, output j

Step 8: For each hidden node, use in a step 7. to train according to

$$\Delta w_i^k = \alpha\delta^k x_i \tag{2.6}$$

Where: Δw_i^k = weight change between i and k

α = learning rate

x_i = input vector i

2.2.3 Social Network Analysis

Definition

Social Network Analysis (SNA) (Scoth J., 2007) is the cartography of interaction social pattern between a member of the organization such as people, team, organizations, etc. There are two ways of data representations methods: graphical and mathematical methods. Normally, the communications internal organization cannot show the relationship between members, but SNA can be depicted the social network by using Sociomatrix, in which the social entities are represented as the points in two-dimensional space and the relationships among pairs of them are represented by the lines, which link the corresponding points.

	A	B	C	D	E
A	-	1	0	0	1
B	1	-	1	1	1
C	0	1	-	1	0
D	0	1	1	-	0
E	1	1	0	0	-

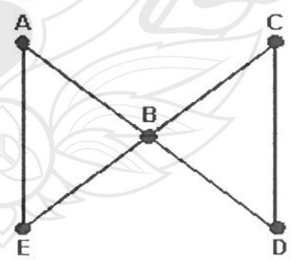

Figure 2-7 Sociomatrix and Sociogram (Scoth J., 2007)

Figure 2-7 shows the sociomatrix and sociogram. The nodes represent the members; 'A','B','C','D','E', while the undirected connection between 5 members represent the communication among members. Each member can connect to other members but not themselves.

Social Network Measurements

SNA provides the mathematical model to describe the network position of individual in social network and these measurements are used through this project including degree of centrality, closeness and betweenness.

Degrees of centrality is defined as a number of direct connections to others. The normalized version simply divides by the maximum degree possible, which is n-1, when n is the total number of nodes. It represents the popularity of the leader.

$$c_{D(x)} = \text{degree of actor x} \tag{2.7}$$

The normalized one is defined as

$$C_{D(x)} = \frac{c_{D(x)}}{n-1} \tag{2.8}$$

Where: $C_{D(x)}$ = Degree of centrality of node x

n = amount of members in team

Betweenness identifies if the actor lies on several paths among other pairs of actors. Such actor has the control over the flow of information in the network. It is the sum of probabilities across all possible pairs of actors, that the shortest path between y and z will pass through actor x. It represents the internal inference of the leader to the other members.

$$c_B(x) = \sum_{y<z} \frac{\text{\# of shortest paths between y and z}}{\text{\# of shortest paths between y and z through actor z}} \tag{2.9}$$

Where : # is the sum of probabilities across all possible pair of actors

The normalized on for the undirected network is

$$C_{B(x)} = \frac{c_{B(x)}}{(n-1)(n-2)/2} \tag{2.10}$$

Where: $C_{B(x)}$ = Betweenness of node x

n = the number of the actor

and for the directed network is

$$C_{B(x)} = \frac{c_{B(x)}}{(n-1)(n-2)} \tag{2.11}$$

Where: $C_{B(x)}$ = Betweenness of node x

n = the number of the actor

Closeness focuses on how close an actor is to all other actors in the set of actors. The idea is that an actor is central if it can quickly interact with all others. If the actors in the set are engaged in problem solving, and the focus is on communication links, efficient solutions occur when one actor has very short communication paths to the others. Alternatively, closeness is an inverse measure of degree: the large numbers, the more distant an actor is.

$$c_{C(x)} = \frac{1}{\sum_{y \in U} d(x,y)} \tag{2.12}$$

Where $d(x, y)$ is the length of shortest path between actor x and actor y, U is the set of all actors. And the normalized one is defined as

$$C_{c(x)} = (n-1) \bullet c_{C(x)} \tag{2.13}$$

Where n is the number of the actor and $c_{C(x)}$ from (2.12).

The hypothesis of this research is that the leader has maximum of degree of centrality, closeness and betweeness. More specifically, it can conclude that the member who is the most active person, the most influence and being the closest to other members can be considered as the leader.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Research Methodology

In this chapter, research methodology is explained to provide more detail about the procedure of approach for role classification of a collaborative learning team. This research designs the experiment to obtain the leadership perception of team members. The pilot study is limited to the extent of experience in assigning topic and teamwork of team members affect the collaborations on the web-based collaborative learning workspace. In this project, FLE (Future Learning Environment) is used as the web-based collaborative learning workspace. The discussion board, where team members exchange their ideas through the posted messages, is investigated. The experiment and design are shown later.

Moreover, neural network is important for role classification of a collaborative learning team. Software agent which developed by JADE (Java Agent Development Framework) still has significance to separate the team of students. JADE is a software framework in JAVA language. JADE supports the implementation for multi-agent system. The main issue of this research is to develop the agent employing the concept of neural network to classify the team of students to the leaders and the followers automatically.

The research methodology consists of five main steps including:

1. Collecting social network data and role perception data
2. Developing the classifier model
3. Developing the software agent
4. Identifying the effective of the developed software agent
5. Investigating the developed software agent

Figure 3-1 shows some research methodology stages for this research.

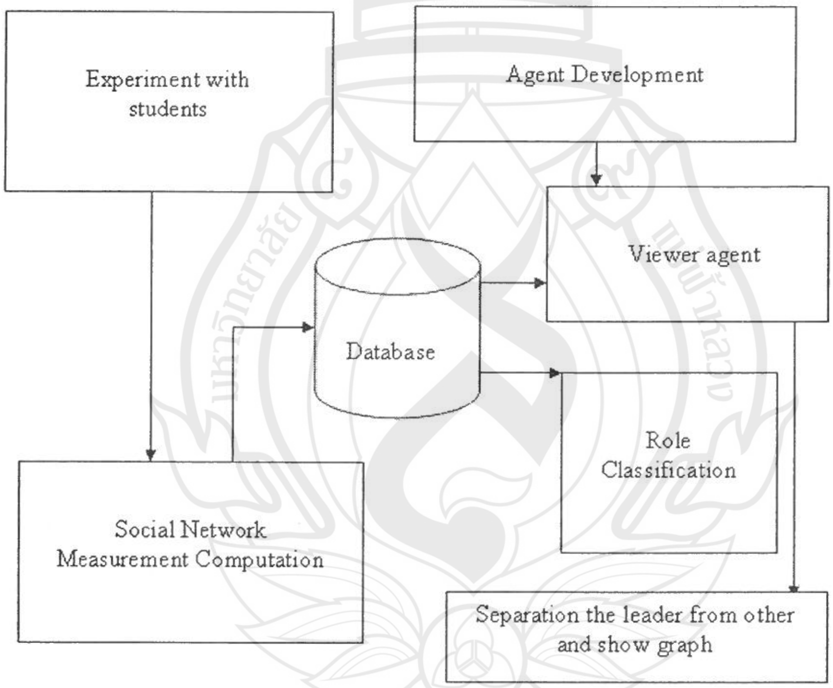

Figure 3-1 Research methodology

3.2 Pilot Studies

The pilot studies are conducted to study how students percept the leadership from team members. Three factors including degree of centrality, closeness and betweeness are thus measured. The experiment is to design in one case study by determining the variety students in each team, the topic experience and the teamwork experience and their parameters including time, amount of members and studied topic which shown in the next section.

3.2.1 Experimental Design

The first step, the students are divided in 5 team of 5 persons. The members are from variety Major from Mae Fah Luang University (MFU). All teams are assigned with un-experienced topic. All teams were supposed to be the nutritionist teams and assigned to propose the vegetarian diet plans for a teenager client, who is 18 years old Lacto-Vegetarian girl having anemia and short term concentration problem. They are expected to propose the plan for a month helping their client keep controlling her weight without any effect from the nutrition lacking. The collaboration session took 10 days.

The second step is the observation of the discussion behavior of members. If the member did not responses, they were encouraged by posting the interesting topic for discussing and being to the consistent with the topic. After that this project collects the connection between people into the matrix. Before the final day, each team would design the diet plan. At the end of collaborative the members were asked who they thought he or she is the leader of the team.

3.2.2 Learning Environment

In this research, FLE3 is chosen to be a software for computer supported collaborative learning (CSCL). Fle3 is a web-based learning environment, open source and free software released under the GNU General Public Licence (GPL) that was developed by Team UIAH Media Lab, University of Art and Design Helsinki. FLE is written in Python. The user interface is shown in Figure 3-2.

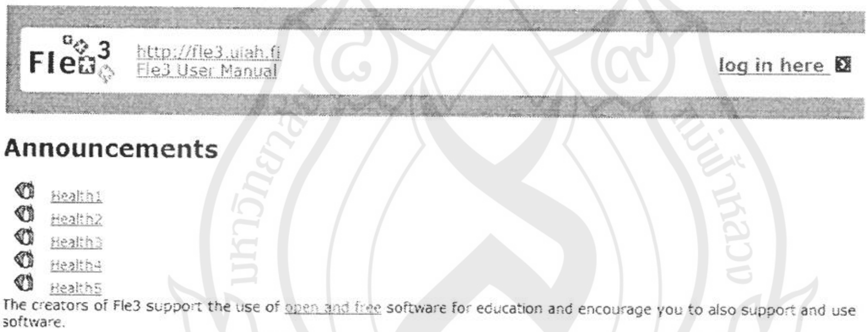

Figure 3-2 FLE web page for experiment

3.2.3 Relation Analysis

In the discussion board, the connections between members were non-directional graph, this project analyzes the link. The values on each link represent the interaction frequency among team members (UIAH Media Lab, 2007). The frequency value was incremented every time a member responded to another member's posted message as shown in Figure 3-3.

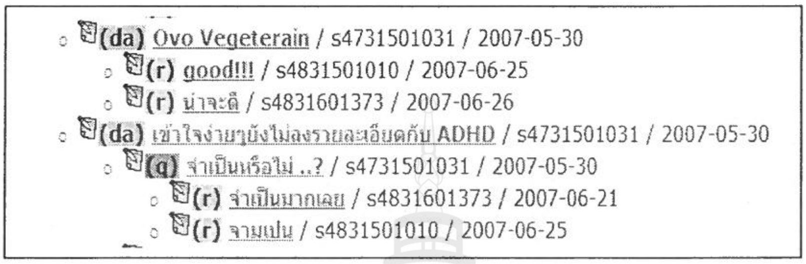

Figure 3-3 Occurrence of interactions among team members from posted message in discussion board

Figure 3-3 shows the collaborative connections found in discussion board. For example s4731501031 posts some question and then s4831501010 responds the answer. Therefore, there is the connection between s4731501031 and s4831501010. At the same time s4831601373 answer the question of s4731501031. There is the connection between s4731501031 and s4831601373 too. The number of connection is represented as the weight of link. Finally the sociomatrix as shown in Figure 3-4(b) can be drawn as the sociogram in Figure 3-4 (a).

S431501031&S4831501010
S431501031&S4831601373

	31	10	373
31	0	2	2
10	2	0	0
373	2	0	0

(a) (b)

Figure 3-4 Sociogram(a) and Sociomatrix(b)

Figure 3-4 (b), the degree of centrality of s4731501031 is maximum which is equal to 2.0. s4731501031 has the most connections in network causing s4731501031 is the most popular in the team. s4731501031 has maximum closeness, which equals to 1. It means that s4731501031 close to everyone. Finally, s4731501031 has maximum betweeness, which is equal to 0.25. It shows that, s4731501031 is in between two important constituencies.

3.3 Agent Implementation

JADE is chosen in the research to implement the agent displaying user interface to the actual instructor. The following steps demonstrate how to install JADE to the system.

1. Java Development Kit (JDK) is installed
2. JADE has extra library file. The extracted file is pasted in any directory. For example, JADE library is located in "C:\jade\lib" shows in Figure 3-5.

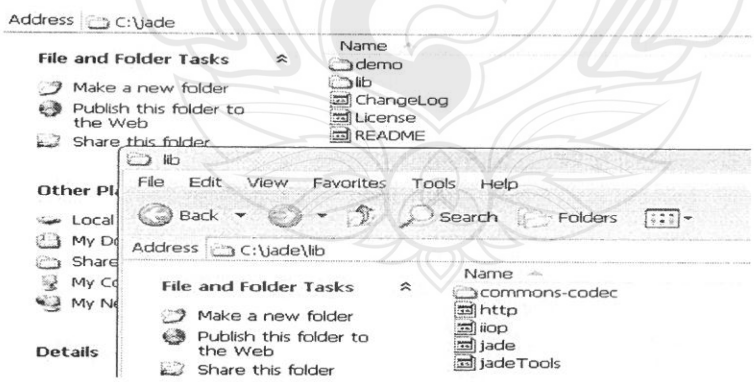

Figure 3-5 JADE library files

3. Running JADE can be tested by typing this in command prompt for setting the path and running JADE monitor.

4. If the result is shown as Figure 3-6, it means JADE is ready to be used.

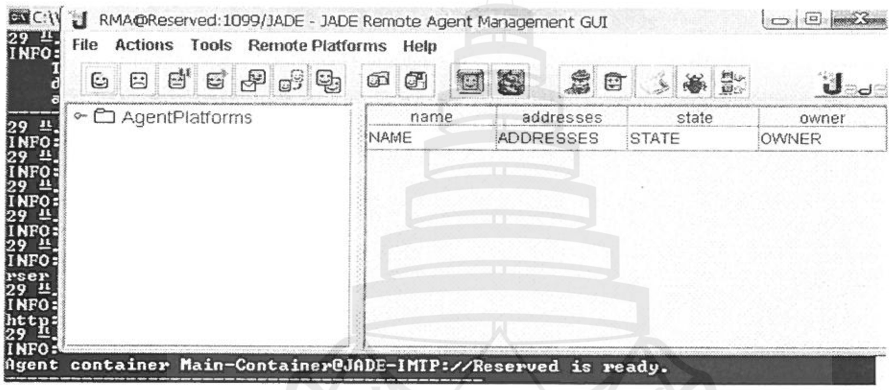

Figure 3-6 JADE interface

Consequently, the followings are the steps for displaying graph pattern by the agent:

1. Start NetBeans and run agent files.

2. Run JADE monitor and start new agent in main container.

3. Get data from Microsoft Access database to draw a graph.

4. Plot lines graph in 2 dimensions.

5. Generate picture of graph which are five lines.

6. Display the result.

All steps of displaying graph pattern is shown in Figure 3-7.

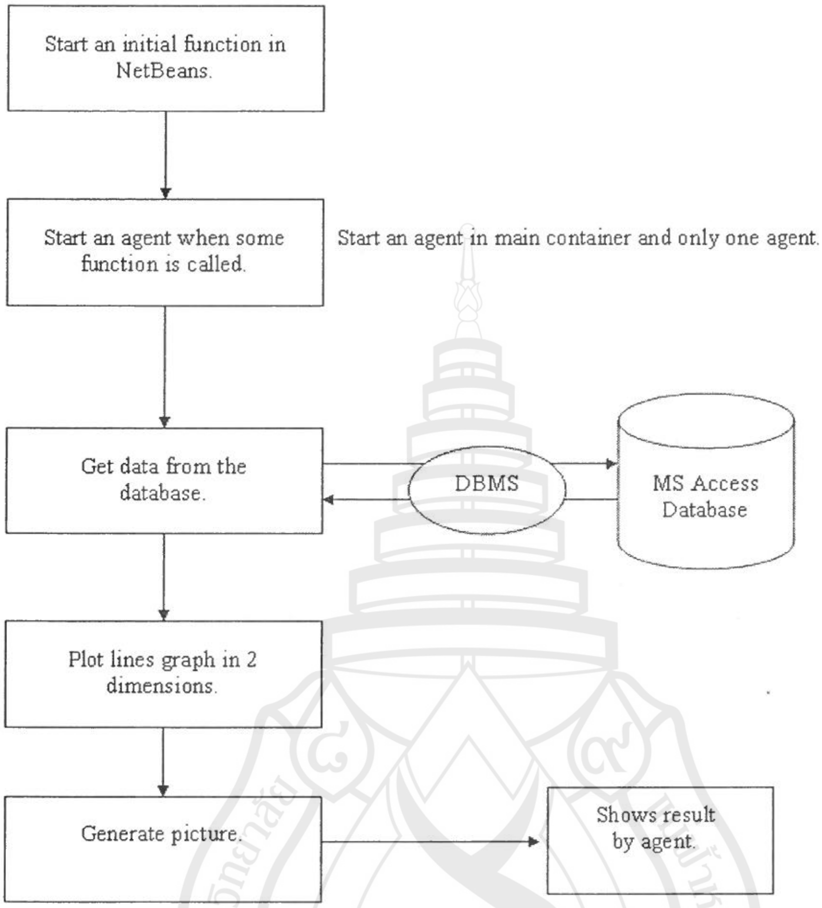

Figure 3-7 Conceptual diagram of graph displaying module

3.4 Role Classification

3.4.1 Training

This research uses the social network analysis measurement including degree of centrality, closeness and betweeness as the training parameters to classify the leader pattern from the collaborative learning team by using back-propagation learning algorithm. The measurement of degree of centrality, closeness and betweeness which are used to train the classifier is shown in appendix A.

3.4.2 Learning Algorithm

As shown that this research chooses back-propagation neural network, which is the supervised learning. Input data and target output is set to neural network. The result of neural network processes is training output. For the next learning, neural network need three input values are input data, target output and training parameter shown in Figure 3-8.

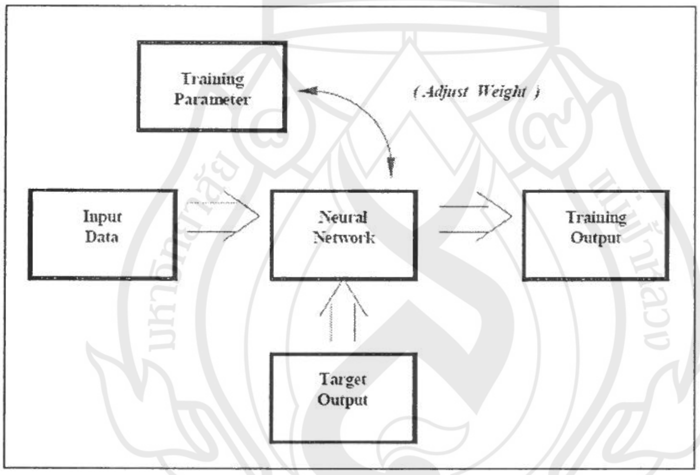

Figure 3-8 The supervised learning (Odell J., 2005)

3.4.3 Network Architecture

This research use 3 layers neural network, having 10 input units, 2 hidden units and 1output unit as show in the Figure 3-9.

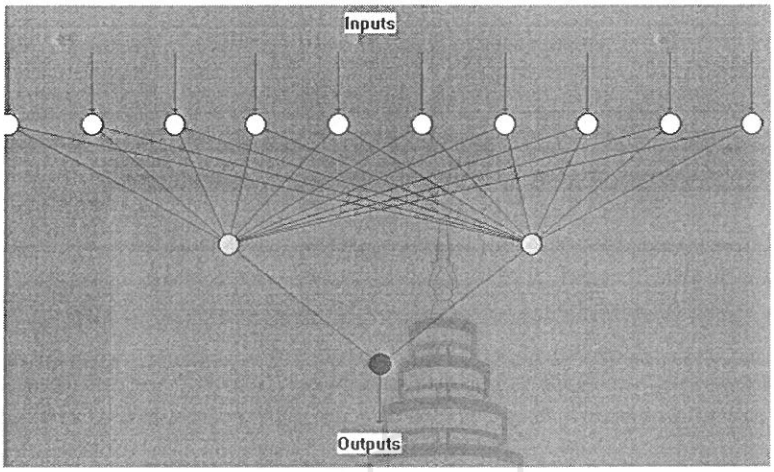

Figure 3-9 The network architecture

3.4.4 Testing

After that neural network is trained the testing pattern from the pilot study is tested. The testing pattern is shown in Appendix B.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Results

Until the end of collaboration session, the sociomatrix is created. Table 4-1 shows an example of sociomatrix of one team from the pilot study (Team 5).

4.1.1 Sociomatrix

The sociomatrix shown in Table 4.1 can be plotted as the sociogram as shown in Figure 4-1.

Table 4-1 Sociomatrix of connection of members in team

26/6/2007	S1	S2	S3	S4	S5
S1	0	6	4	0	1
S2	6	0	14	6	8
S3	4	14	0	6	4
S4	0	6	6	0	4
S5	1	8	4	4	0

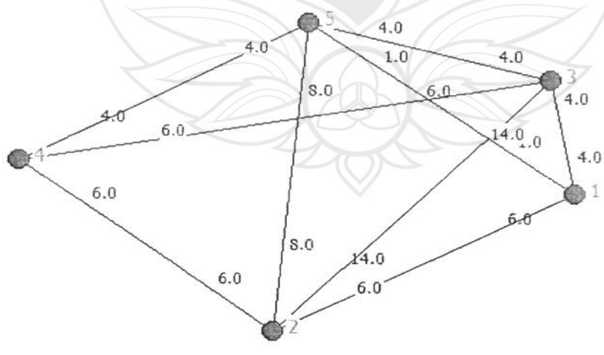

Figure 4-1 Collaboration pattern of Team 5

4.1.2 Collaboration Patterns

From Figure 4.1, the collaboration pattern shows the connection among members and link weight. Node represent the team member S1,S2,S3,S4,S5 respectively. Then all of social network measurements are calculated. Their patterns representing the evolution of each measurement are finally used to train backpropagation neural network.

4.1.3 Degree of Centrality

From the collaboration pattern of team 5, the degree of centrality can be calculated in Table 4-2.

Table 4-2 Degrees of Centrality of Team 5

Date	S1	S2	S3	S4	S5
31/5/2007	0.500	0.000	0.000	0.000	0.500
15/6/2007	0.500	0.000	0.250	0.000	0.250
16/6/2007	0.250	0.000	0.250	0.003	0.250
17/6/2007	0.167	0.056	0.333	0.167	0.167
21/6/2007	0.200	0.050	0.350	0.167	0.150
22/6/2007	0.154	0.038	0.308	0.167	0.192
25/6/2007	0.132	0.342	0.184	0.056	0.158
26/6/2007	0.104	0.321	0.264	0.000	0.160

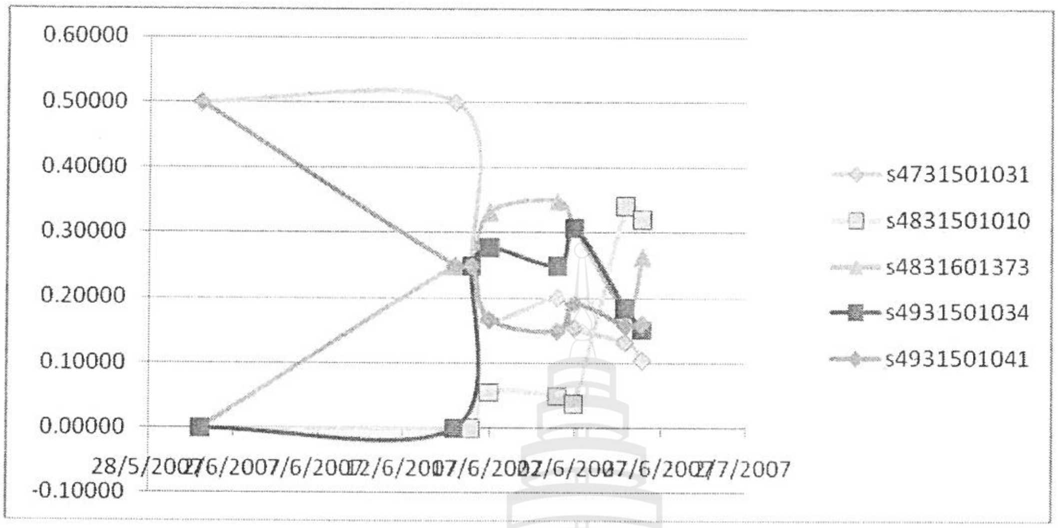

Figure 4-2 The degree of centrality pattern of team5

The graph of the degree of centrality for all members can be plotted as it is shown in Figure 4-2. S1, S2, S3, S4 and S5 are s4731501031, s4831501010, s4831601371, s4931501034, s4931501041 respectively. From Figure 4-2, s4731501031 is the most popular on the first half of collaboration and then s4831601373 become more popular than s4731501031at the second half of collaboration. And the development of s4831601373 gradually increases (This project considers that s4831601373 is the most popularity over time). From the experiment, s4831601373 is voted to the leader but neural network classified s4831601373 and s4931501034 are the leaders. It can be concluded that, neural network classified by the similarity pattern which is not be able to distinguish easily by human.

4.1.4 Closeness

From the collaboration pattern of Team 5, the closeness is calculated in Table 4-3.

Table 4-3 Closeness of Team 5

Date	S1	S2	S3	S4	S5
31/5/2007	0.250	0.200	0.200	0.200	0.250
15/6/2007	0.333	0.200	0.308	0.200	0.308
16/6/2007	0.444	0.200	0.444	0.444	0.444
17/6/2007	0.667	0.500	0.800	0.667	0.571
21/6/2007	0.667	0.500	0.800	0.667	0.571
22/6/2007	0.667	0.500	0.800	0.667	0.571
25/6/2007	0.800	1.000	0.800	0.800	0.800
26/6/2007	0.800	1.000	1.000	0.800	1.000

From Table 4-3, the pattern of closeness can be plotted as shown in Figure 4-3

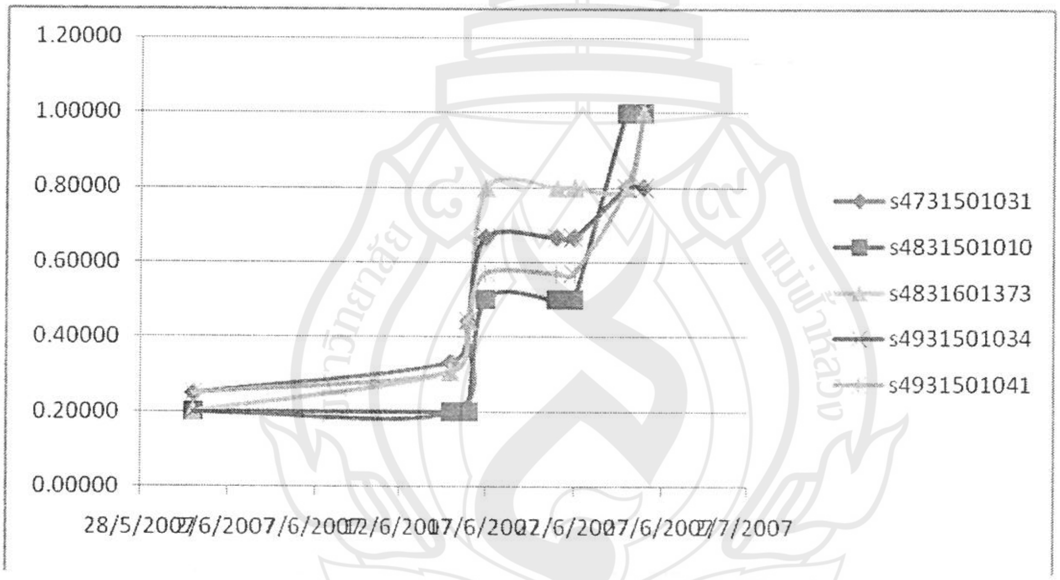

Figure 4-3 The closeness pattern of team5

Table 4-3 shows that s4831601373 is the closest. However, at the end of the collaboration, s4931501041 and s4831501010 have the same pattern of closeness. That means s4831601373 and s4931501041 had the discussion to all members in the team. More specifically, s4831601373 and s4931501041 know everybody in the team.

From the experiment, s4831601373 is voted to the leader; at the same time that neural network classifies s4831601373 as the leader. This result shows that neural network can classify the regarding to the perception of human.

4.1.5 Betweeness

From the collaboration pattern of Team 5, the betweeness are shown in Table 4-4.

Table 4-4 Betweeness of Team 5

Date	S1	S2	S3	S4	S5
31/5/2007	0.000	0.000	0.000	0.000	0.000
15/6/2007	0.167	0.000	0.000	0.000	0.000
16/6/2007	0.003	0.000	0.003	0.003	0.003
17/6/2007	0.167	0.000	0.583	0.167	0.083
21/6/2007	0.167	0.000	0.583	0.167	0.083
22/6/2007	0.167	0.000	0.583	0.167	0.083
25/6/2007	0.056	0.111	0.056	0.056	0.056
26/6/2007	0.000	0.056	0.056	0.000	0.056

The betweeness over the collaboration is shown in Table 4-4 and the graph shows that the most internal influence is s4831601373. It means s4831601373 is the person chosen to connect by other members.

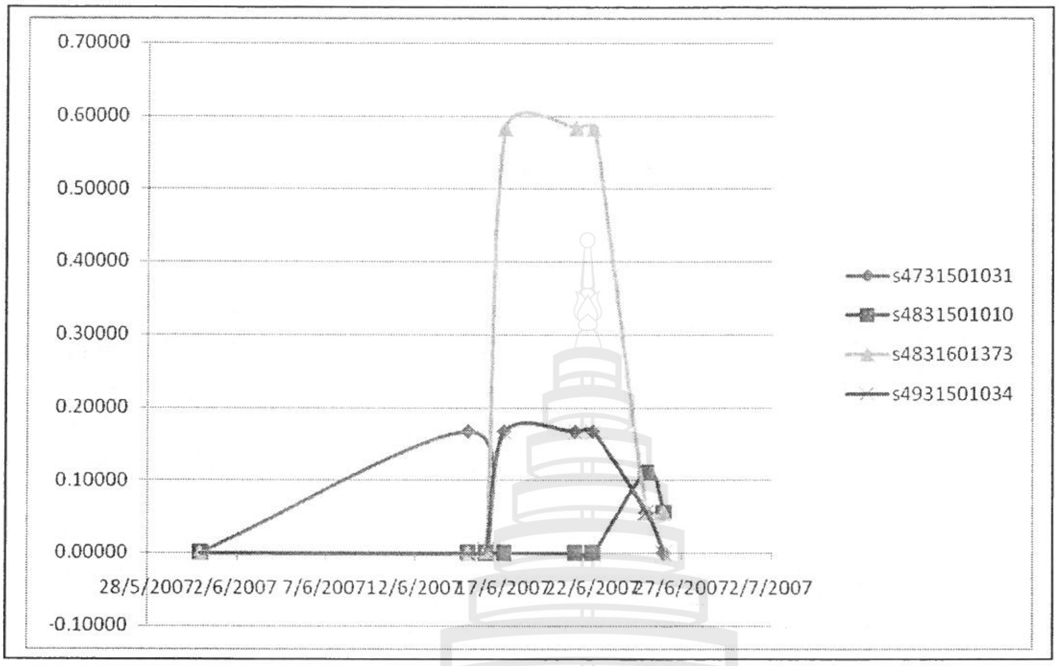

Figure 4-4 The Betweeness pattern of team5

From the experiment, s4831601373 is voted to the leader as the same as neural network classifier.

Table 4-5 shows the result of role classification of collaborative learning team. The voted and classified leaders are compared from 3 measurements including; degree of centrality, closeness and betweeness.

Table 4-5 Role Classification Result

team	voted leader	classified leader by degree of centrality	classified leader by closeness	classified leader by betweeness
1	s4831501001 and M	s4831501001 and M	non leader	non leader
2	por	por and 4831006079	non leader	non leader
3	s4831501008	s4831501008	non leader	non leader
4	korkai	non leader	non leader	non leader
5	s4831601373	s4831601373 and 4931501034	s4831601373	s4831601373

4.2 Graphic User Interface

This research uses NetBeans IDE 5.5 on Microsoft Windows XP to construct an interface which receives input from user for selecting graph format as shown in Figure 4-5. Agent's graphic user interface is shown in Figure 4-6 respectively.

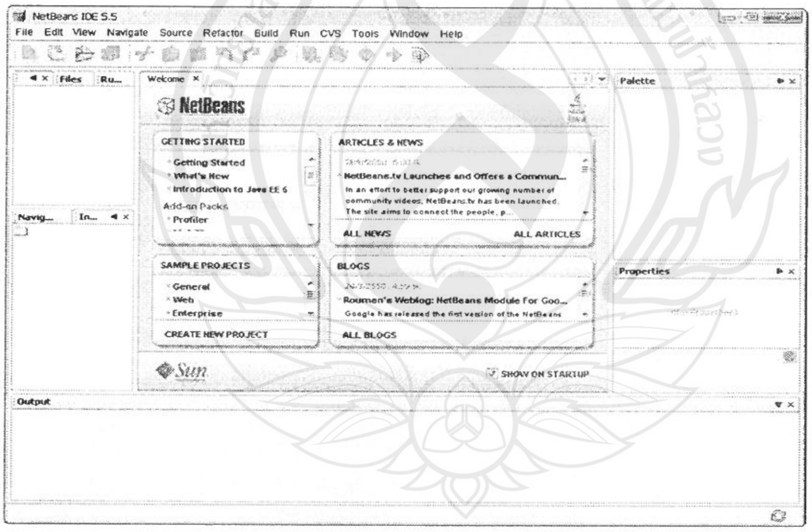

Figure 4-5 Netbeans IDE 5.5 interface

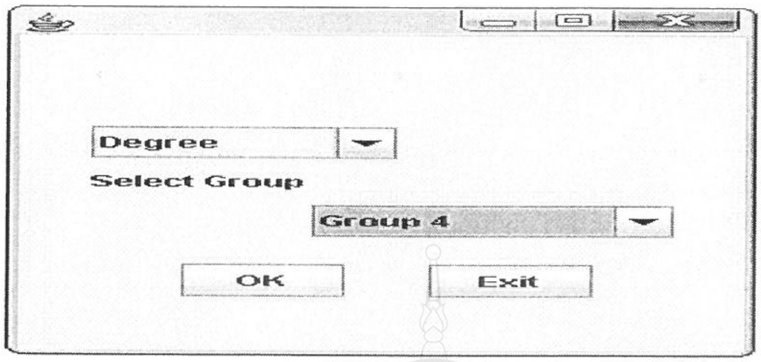

Figure 4-6 Selectable graph GUI

Example result by Agent

The graphs below (Figure 4-7, 4-8 and 4-9) are the examples of the social network measurements of Team 5 plotted by developed agent.

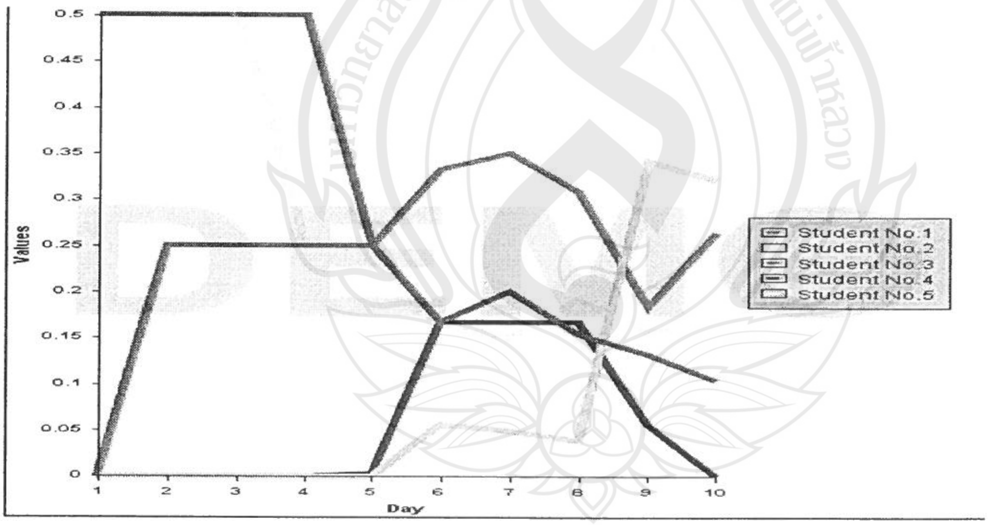

Figure 4-7 Degree of centrality plotted by developed agent

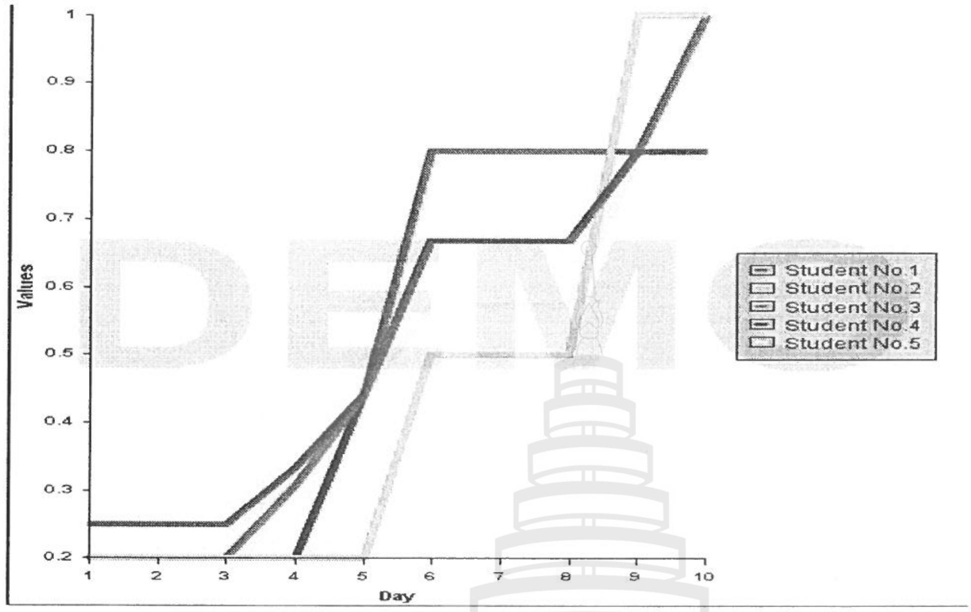

Figure 4-8 Closeness plotted by developed agent

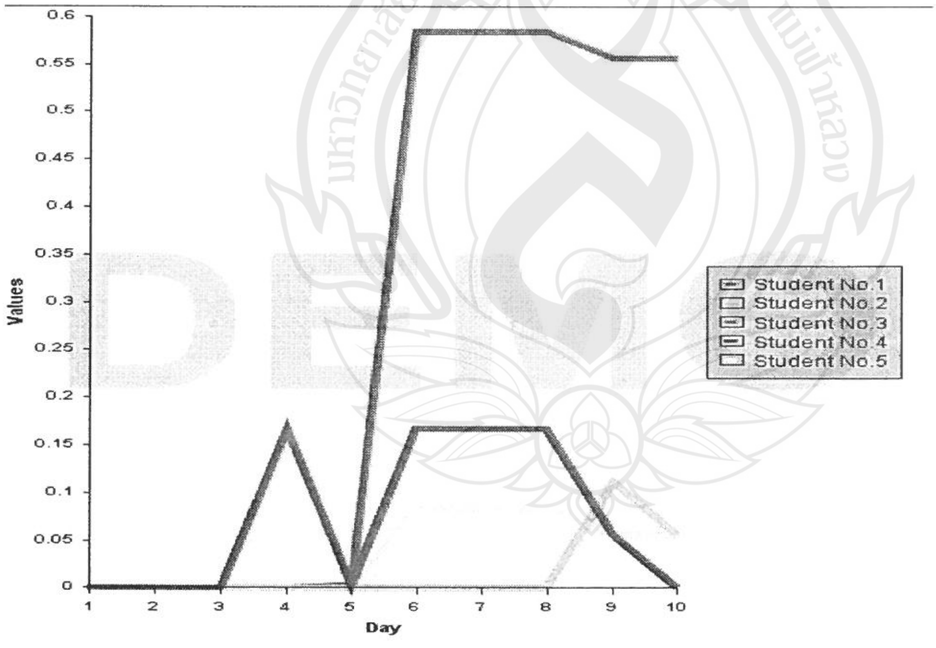

Figure 4-9 Betweeness plotted by developed agent

4.3 Discussion

The example above is one of the best cases from the experiment which the patterns of all measurements are perfect enough for classifying. However, this is also the non-perfect case.

Degree of centrality

Figure 4-10 shows the degree of centrality of Team 1.

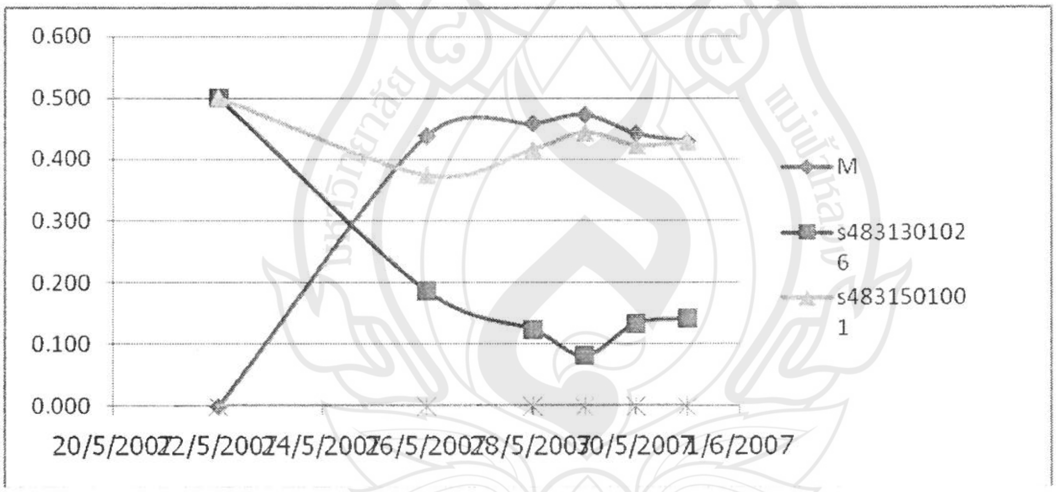

Figure 4-10 The degree of centrality of Team 1

From Figure 4-10, M and s4831501001 were voted to be the leader. The neural network also classified them as the leader.

Closeness

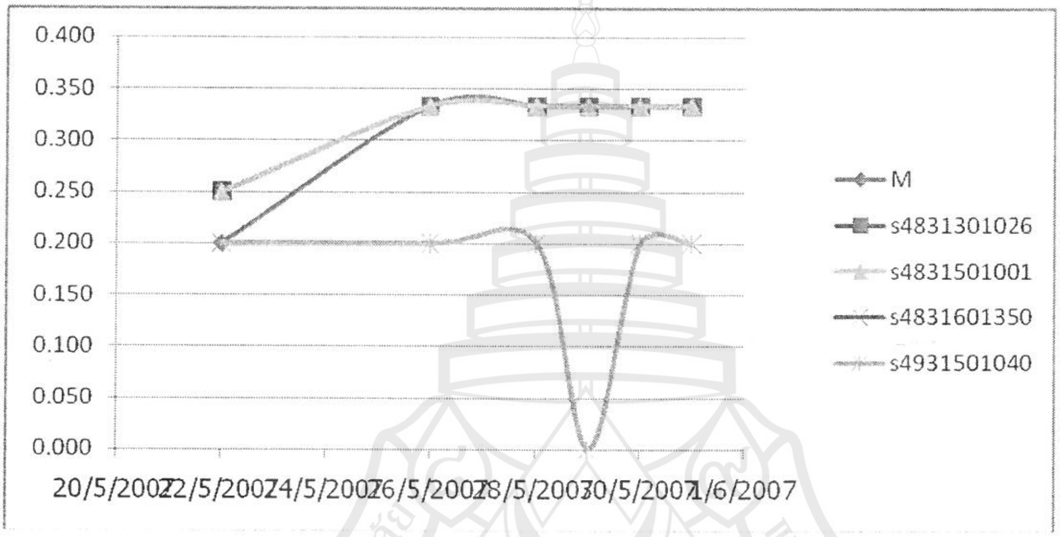

Figure 4-11 The closeness of Team 1

From Figure 4-11, M and s4831501001 was voted to be the leader but neural network couldn't classify anybody to the leader. The reason might be because the maximum variable of M and s4831501001 is not high enough to be considered as the leader.

Betweeness

Figure 4.12 shows that all betweenness is constant which is equal to zero. It is non-perfect case and it is not selected for analyzing. Neural Network does not classify anybody in the team as the leader from this pattern. It can be concluded that the value and the similarity of the pattern affect the classification of neural network.

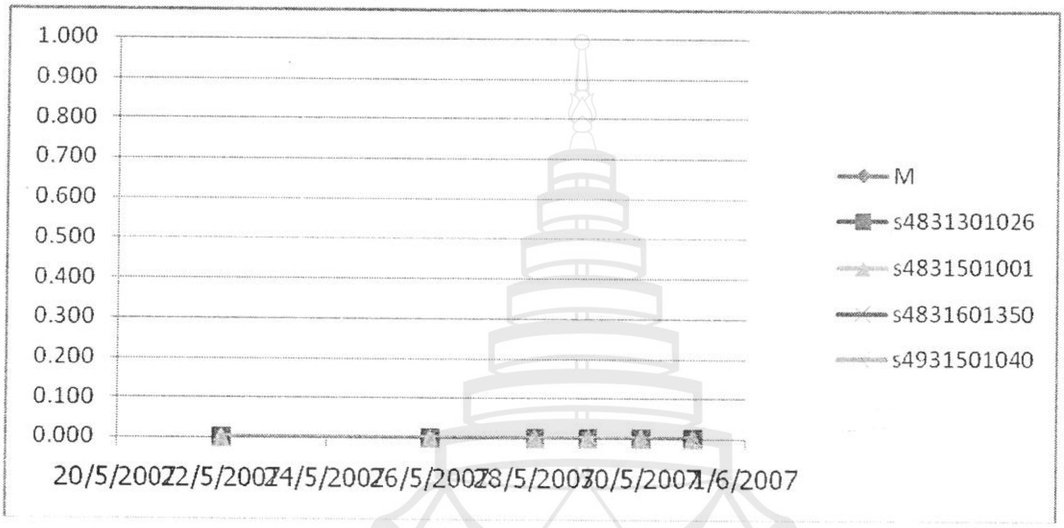

Figure 4-12 The betweeness of Team 1

In conclusion, the neural network based agent can effectively classify the leader according to the leadership perception of team members. After testing with 27 testing patterns, Table 4-6 shows the accuracy of the proposed agent for all patterns of measurements.

Table 4-6 Accuracy of the developed agent

Patterns of Measurements	Classifying Accuracy
Degree of Centrality	94.4%
Closeness	64.7%
Betweenness	70.6%

CHAPTER 5

CONCLUSION

5.1 Conclusion

This research considers how student perceive the leadership of team members. Three measurements including degree of centrality, closeness and betweeness are investigated in what extent they can represent the leadership perception of team members. The hypothesis of this research is the leader has the significant patterns of those three measurements. Additionally, the agents based approach for role classification of collaborative learning team is developed by employing the concept of justify neural network to classify the leader from the teams.

The designed experiment provides the team of variety students with the inexperienced topic. The collaboration pattern from the experiment is calculated by using social network analysis (SNA). The member, who has the most degree of centrality, is the most popularity over time of collaborative learning. The member, who has the most closeness, is the most closest to everybody. The member, who has the high values of betweeness over the collaboration time, is the most influence person in the team. Three of SNA measurements are used, as the classified pattern in this project.

The objective of this research is to develop an agent based approach employing the neural network for precisely classify the leader from other team members of a collaborative learning team. This research applies backpropagation for a training algorithm. The percentages of testing are 94.4% from the pattern of degree of centrality, 64.7% from the pattern of closeness and 70.6% from the pattern of betweeness. It can be concluded that degree of centrality is the most reliability.

It can be noticed from this research that team members usually can memorize more precisely during the second half of the collaboration time. Moreover, the neural network classifier performs the classification task based on the magnitude and the pattern of data.

5.2 Suggestion

For obtaining more classification accuracy, the unsupervised learning model to classify the similarity of the patterns to investigate whether or no the magnitude of the measurements affect the classification result.

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APPENDIX A

TRAINING PATTERNS

A.1 Degree of centrality

Table A-1 Degree of centrality

name	day 1	day 2	day 3	day 4	day 5	day 6	day 7	day 8	day 9	day 10	bias	target
nang	0.000	0.000	0.000	0.000	0.091	0.067	0.059	0.079	0.056	0.083	1.000	0.000
au	0.333	0.375	0.400	0.429	0.318	0.333	0.324	0.289	0.333	0.333	1.000	0.000
ochini	0.333	0.375	0.300	0.286	0.364	0.400	0.353	0.342	0.278	0.250	1.000	1.000
suchira	0.333	0.250	0.300	0.286	0.227	0.200	0.235	0.263	0.241	0.233	1.000	0.000
benchapol	0.000	0.000	0.000	0.000	0.000	0.000	0.029	0.026	0.093	1.000	1.000	0.000
au	0.500	0.500	0.500	0.417	0.389	0.350	0.333	0.308	0.267	0.250	1.000	0.000
aoo	0.500	0.375	0.300	0.333	0.333	0.350	0.333	0.346	0.333	0.313	1.000	1.000
fon	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.033	0.031	1.000	0.000
lim	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.038	0.067	0.094	1.000	0.000
thanapol	0.000	0.125	0.200	0.250	0.278	0.300	0.333	0.308	0.300	0.313	1.000	0.000
Jade	0.000	0.167	0.200	0.143	0.125	0.143	0.139	0.190	0.200	0.195	1.000	0.000
akira	0.000	0.000	0.000	0.143	0.125	0.074	0.056	0.035	0.071	0.085	1.000	0.000
benz	0.500	0.167	0.200	0.143	0.188	0.214	0.250	0.224	0.214	0.220	1.000	0.000
mae	0.500	0.500	0.500	0.143	0.500	0.429	0.444	0.431	0.414	0.390	1.000	1.000
mom0taro	0.000	0.167	0.100	0.143	0.063	0.143	0.111	0.121	0.100	0.110	1.000	0.000

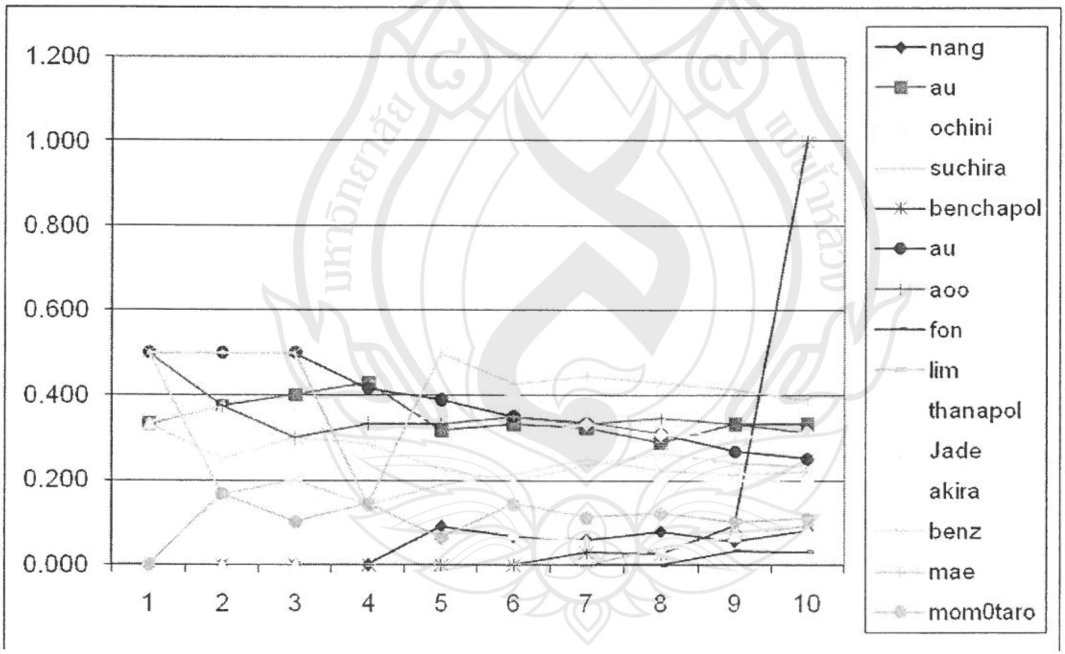

Figure A-1 Degree of centrality patterns

A.2 Closeness

Table A-2 Closeness

name	day 1	day 2	day 3	day 4	day 5	day 6	day 7	day 8	day 9	day 10	bias	target
Jade	0.200	0.400	0.400	0.571	0.571	0.667	0.667	0.800	1.000	1.000	1.00	0.000
akira	0.200	0.200	0.200	0.571	0.571	0.571	0.571	0.571	0.667	1.000	1.00	0.000
benz	0.250	0.400	0.400	0.571	0.571	0.800	0.800	0.800	0.800	1.000	1.00	0.000
mae	0.250	0.500	0.500	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.00	1.000
mom0taro	0.200	0.400	0.400	0.571	0.571	0.667	0.667	0.800	0.800	1.000	1.00	0.000
au	0.250	0.333	0.333	0.333	0.333	0.333	0.333	0.444	0.667	0.667	1.00	0.000
aoo	0.250	0.308	0.308	0.333	0.333	0.333	0.333	0.500	0.800	0.800	1.00	1.000
fon	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.500	0.571	1.00	0.000
lim	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.400	0.500	0.667	1.00	0.000
thanapol	0.200	0.308	0.308	0.308	0.333	0.333	0.333	0.444	0.800	1.000	1.00	0.000
nang	0.200	0.200	0.200	0.200	0.400	0.400	0.500	0.667	0.667	0.800	1.00	0.000
au	0.333	0.333	0.333	0.333	0.444	0.444	0.667	0.667	0.800	1.000	1.00	0.000
ochin	0.333	0.333	0.333	0.333	0.500	0.500	0.800	0.800	1.000	1.000	1.00	1.000
suchira	0.333	0.333	0.333	0.333	0.444	0.444	0.800	1.000	1.000	1.000	1.00	0.000
benchaphol	0.200	0.200	0.200	0.200	0.200	0.200	0.500	0.571	0.800	0.800	1.00	0.000

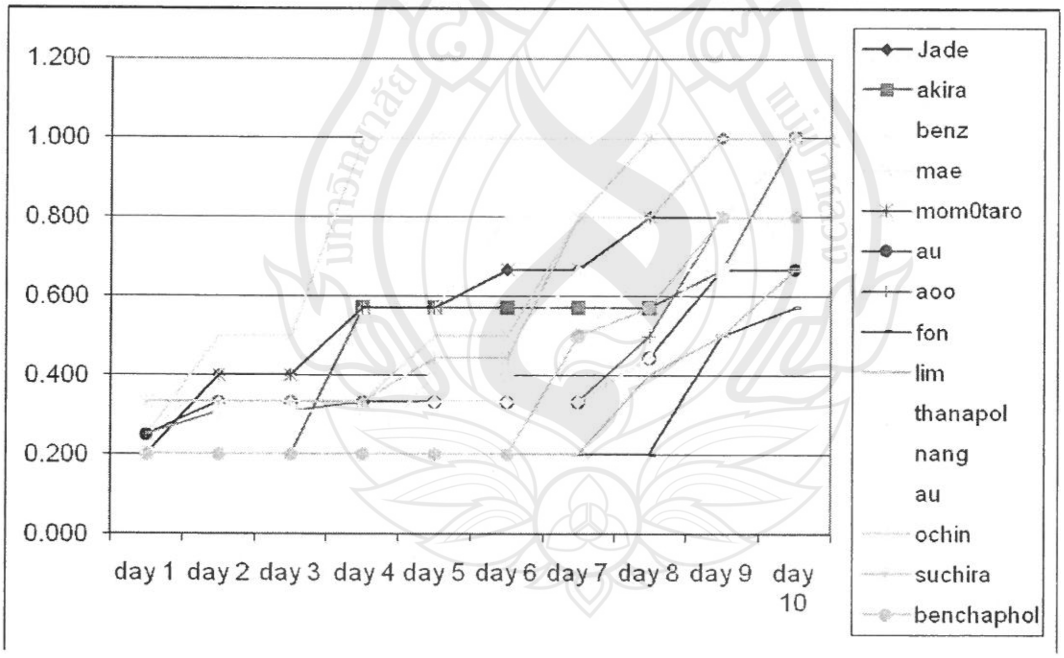

Figure A-2 The pattern of Closeness

A-3 Betweeness

Table A-3 Betweeness

name	day 1	day 2	day 3	day 4	day 5	day 6	day 7	day 8	day 9	day 10	bias	target
nang	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.00	0.000
au	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.00	0.000
ochin	0.000	0.000	0.000	0.000	0.300	0.300	0.500	0.830	0.167	0.056	1.00	1.000
suchira	0.000	0.000	0.000	0.000	0.000	0.000	0.500	0.583	0.167	0.056	1.00	0.000
benchaphol	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.00	0.000
au	0.000	0.167	0.167	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.00	0.000
aoo	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.333	0.500	0.083	1.00	1.000
fon	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.00	0.000
lim	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.00	0.000
thanapol	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.500	0.583	1.00	0.000
Jade	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.167	0.000	1.00	0.000
akira	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.00	0.000
benz	0.000	0.000	0.000	0.000	0.000	0.833	0.833	0.000	0.000	0.000	1.00	0.000
mae	0.000	0.500	0.500	1.000	1.000	0.583	0.583	0.500	0.167	0.000	1.00	1.000
mom0taro	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.00	0.000

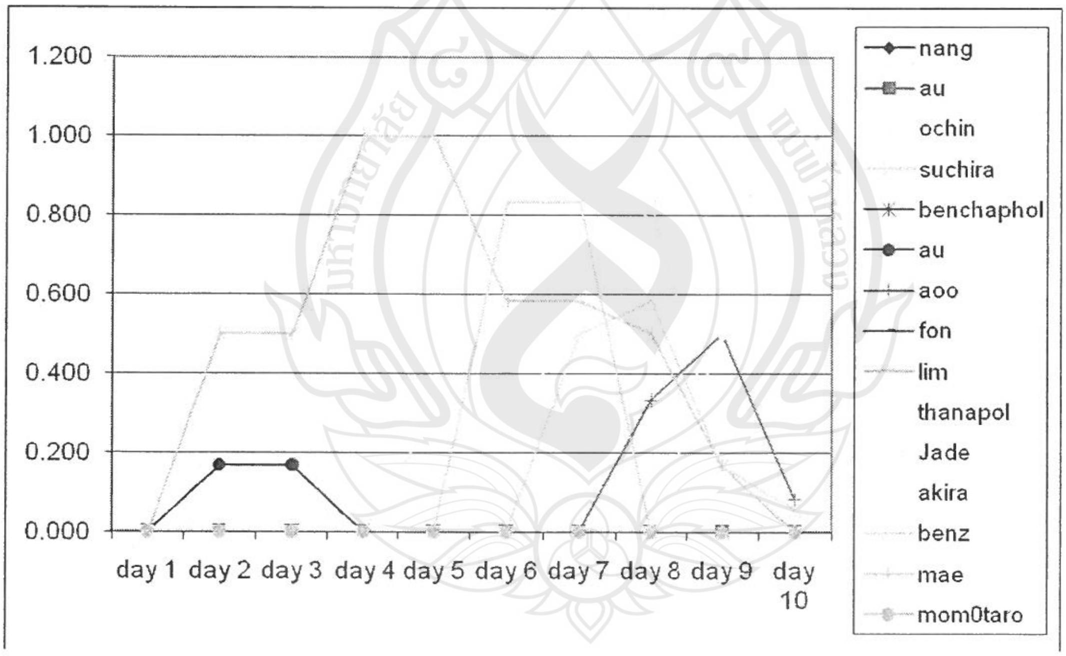

Figure A-3 The patterns of Betweeness

APPENDIX B

TESTING PATTERNS

B.1 Degree of centrality

Table B-1 The degree of centrality.

degree	day 1	day 2	day 3	day 4	day 5	day 6	day 7	day 8	day 9	day 10	bias	target
M	0.000	0.000	0.000	0.000	0.438	0.438	0.458	0.472	0.442	0.429	1.000	1.000
s4831301026	0.500	0.500	0.500	0.500	0.188	0.188	0.123	0.083	0.135	0.143	1.000	0.000
s4831501001	0.500	0.500	0.500	0.500	0.375	0.375	0.417	0.444	0.423	0.429	1.000	1.000
s4831006079	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	1.000	0.000
por	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	1.000	1.000
s4731501043	0.000	0.000	0.100	0.100	0.100	0.100	0.091	0.091	0.091	0.029	1.000	0.000
s4831006027	0.500	0.500	0.100	0.100	0.100	0.100	0.136	0.136	0.136	0.357	1.000	0.000
s4831301075	0.000	0.000	0.350	0.350	0.350	0.350	0.318	0.318	0.318	0.157	1.000	0.000
s4831501008	0.500	0.500	0.450	0.450	0.450	0.450	0.455	0.455	0.455	0.457	1.000	1.000
korkai	0.500	0.500	0.500	0.500	0.400	0.400	0.400	0.400	0.400	0.400	1.000	1.000
s4931402021	0.500	0.500	0.500	0.500	0.300	0.300	0.300	0.300	0.300	0.300	1.000	0.000
s4931501006	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000
s4731501031	0.500	0.500	0.500	0.500	0.250	0.167	0.200	0.154	0.132	0.104	1.000	0.000
s4831501010	0.000	0.000	0.000	0.000	0.000	0.056	0.050	0.038	0.342	0.321	1.000	0.000
s4831601373	0.000	0.000	0.000	0.250	0.250	0.333	0.350	0.308	0.184	0.264	1.000	1.000
s4931501034	0.000	0.000	0.000	0.000	0.250	0.278	0.250	0.308	0.184	0.151	1.000	0.000
s4931501041	0.500	0.500	0.500	0.250	0.250	0.167	0.150	0.192	0.158	0.160	1.000	0.000

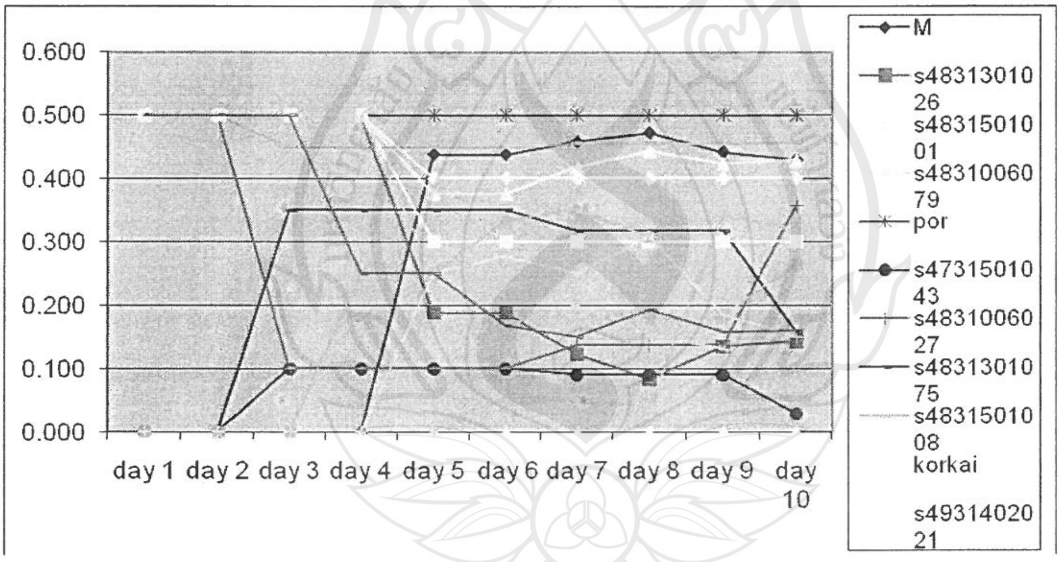

Figure B-1 Patterns of degree of centrality

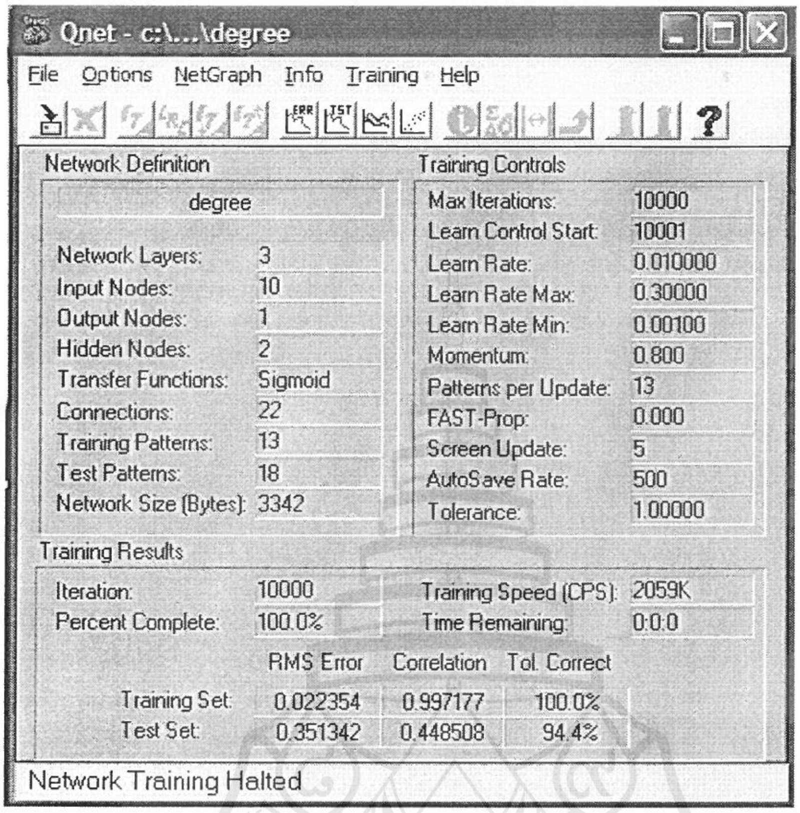

Figure B-2 Result of degree of centrality

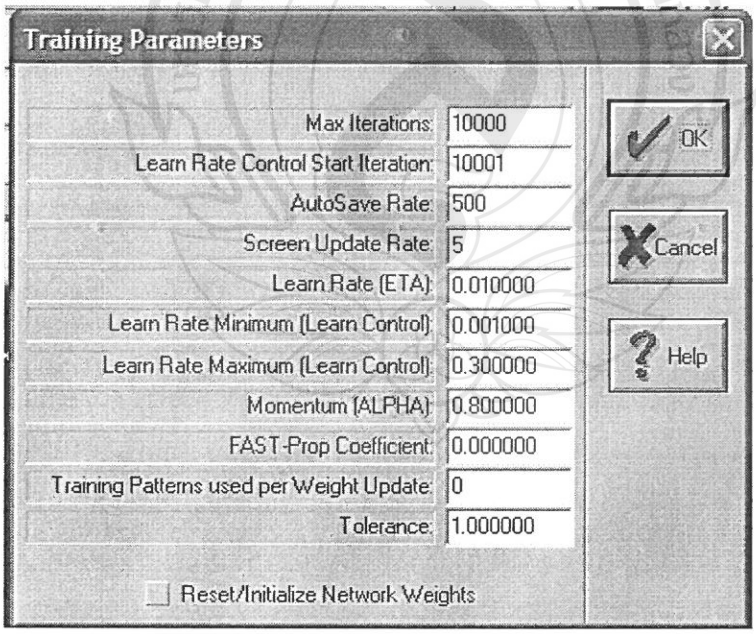

Figure B-3 Training Parameters

Targets and Network Outputs
Network Name: degree
Iterations: 10000
(Note: * = Test Pattern)

1 =>	Output Node 1	(target,output) =	0.00000,	0.05435
2 =>	Output Node 1	(target,output) =	1.00000,	0.89339
3 =>	Output Node 1	(target,output) =	0.00000,	-0.02798
4 =>	Output Node 1	(target,output) =	0.00000,	-0.09436
5 =>	Output Node 1	(target,output) =	0.00000,	0.13898
6 =>	Output Node 1	(target,output) =	1.00000,	0.80267
7 =>	Output Node 1	(target,output) =	0.00000,	-0.10072
8 =>	Output Node 1	(target,output) =	0.00000,	-0.09474
9 =>	Output Node 1	(target,output) =	0.00000,	0.12754
10 =>	Output Node 1	(target,output) =	0.00000,	-0.06593
11 =>	Output Node 1	(target,output) =	0.00000,	-0.08748
12 =>	Output Node 1	(target,output) =	0.00000,	0.16966
13 =>	Output Node 1	(target,output) =	1.00000,	1.09489
14 =>	Output Node 1	(target,output) =	0.00000,	-0.04466
15*=>	Output Node 1	(target,output) =	1.00000,	1.17719
16*=>	Output Node 1	(target,output) =	0.00000,	-0.11545
17*=>	Output Node 1	(target,output) =	1.00000,	0.35523
18*=>	Output Node 1	(target,output) =	0.00000,	0.98356
19*=>	Output Node 1	(target,output) =	1.00000,	0.98356
20*=>	Output Node 1	(target,output) =	0.00000,	-0.09979
21*=>	Output Node 1	(target,output) =	0.00000,	0.85623
22*=>	Output Node 1	(target,output) =	0.00000,	-0.09265
23*=>	Output Node 1	(target,output) =	1.00000,	0.97103
24*=>	Output Node 1	(target,output) =	1.00000,	0.35672
25*=>	Output Node 1	(target,output) =	0.00000,	-0.01990
26*=>	Output Node 1	(target,output) =	0.00000,	-0.10219
27*=>	Output Node 1	(target,output) =	0.00000,	-0.11059
28*=>	Output Node 1	(target,output) =	0.00000,	-0.05180
29*=>	Output Node 1	(target,output) =	1.00000,	0.53118
30*=>	Output Node 1	(target,output) =	0.00000,	0.83769
31*=>	Output Node 1	(target,output) =	0.00000,	-0.07074

B.2 Closeness

Table B-2 Closeness

closeness	day 1	day 2	day 3	day 4	day 5	day 6	day 7	day 8	day 9	day 10	bias	target
M	0.200	0.200	0.200	0.200	0.333	0.333	0.333	0.333	0.333	0.333	1.000	1.000
s4831301026	0.250	0.250	0.250	0.250	0.333	0.333	0.333	0.333	0.333	0.333	1.000	0.000
s4831501001	0.250	0.250	0.250	0.250	0.333	0.333	0.333	0.333	0.333	0.333	1.000	1.000
s4831006079	0.250	0.250	0.250	0.250	0.250	0.250	0.250	0.250	0.250	0.250	1.000	0.000
por	0.250	0.250	0.250	0.250	0.250	0.250	0.250	0.250	0.250	0.250	1.000	1.000
s4731501043	0.200	0.200	0.444	0.444	0.444	0.444	0.444	0.444	0.444	0.444	1.000	0.000
s4831006027	0.250	0.250	0.400	0.400	0.400	0.400	0.400	0.400	0.400	0.444	1.000	0.000
s4831301075	0.200	0.200	0.444	0.444	0.444	0.444	0.444	0.444	0.444	0.500	1.000	0.000
s4831501008	0.250	0.250	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	1.000	1.000
korkai	0.250	0.250	0.250	0.250	0.333	0.333	0.333	0.333	0.333	0.333	1.000	1.000
s4931402021	0.250	0.250	0.250	0.250	0.333	0.333	0.333	0.333	0.333	0.333	1.000	0.000
s4931501006	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200	1.000	0.000
s4731501031	0.250	0.250	0.250	0.333	0.444	0.667	0.667	0.667	0.800	0.800	1.000	0.000
s4831501010	0.200	0.200	0.200	0.200	0.200	0.500	0.500	0.500	1.000	1.000	1.000	0.000
s4831601373	0.200	0.200	0.200	0.308	0.444	0.800	0.800	0.800	0.800	1.000	1.000	1.000
s4931501034	0.200	0.200	0.200	0.200	0.444	0.667	0.667	0.667	0.800	0.800	1.000	0.000
s4931501041	0.250	0.250	0.250	0.308	0.444	0.571	0.571	0.571	0.800	1.000	1.000	0.000

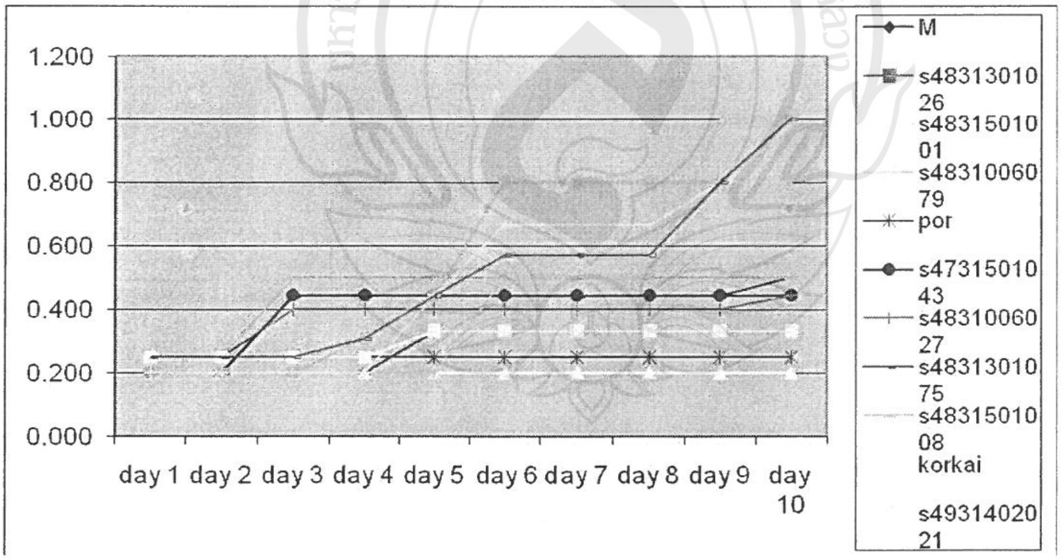

Figure B-4 The patterns of closeness

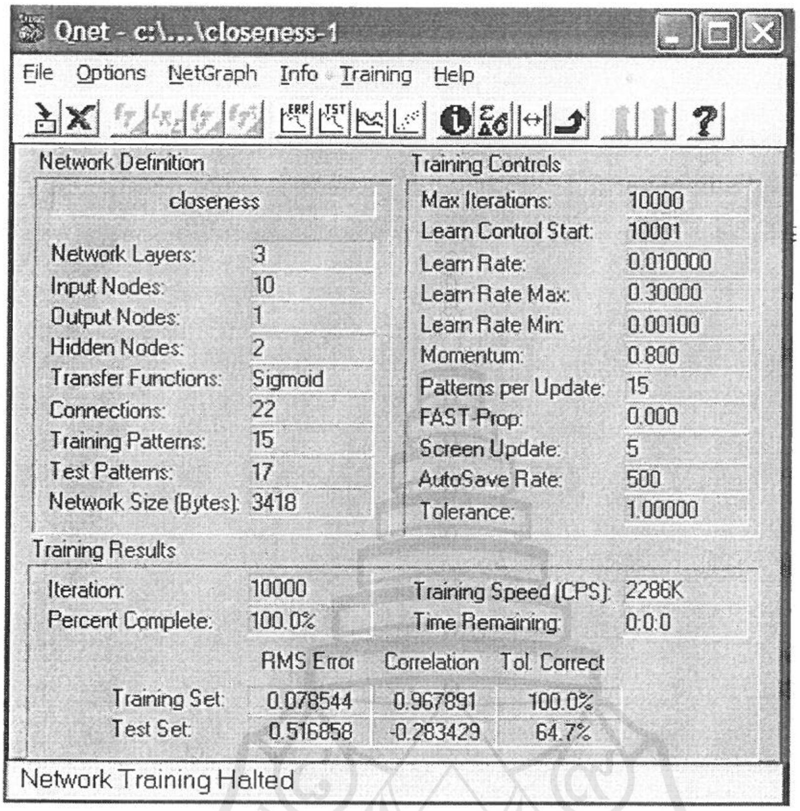

Figure B-5 Result of closeness

Targets and Network Outputs
Network Name: closeness
Iterations: 10000
(Note: * = Test Pattern)

1 =>	Output Node 1	(target,output) =	0.00000,	0.09056
2 =>	Output Node 1	(target,output) =	0.00000,	0.05568
3 =>	Output Node 1	(target,output) =	0.00000,	-0.18308
4 =>	Output Node 1	(target,output) =	1.00000,	0.94459
5 =>	Output Node 1	(target,output) =	0.00000,	-0.18718
6 =>	Output Node 1	(target,output) =	0.00000,	0.12646
7 =>	Output Node 1	(target,output) =	1.00000,	0.88150
8 =>	Output Node 1	(target,output) =	0.00000,	0.00069
9 =>	Output Node 1	(target,output) =	0.00000,	-0.17322
10 =>	Output Node 1	(target,output) =	0.00000,	-0.02567
11 =>	Output Node 1	(target,output) =	0.00000,	-0.17609
12 =>	Output Node 1	(target,output) =	0.00000,	0.01921
13 =>	Output Node 1	(target,output) =	1.00000,	0.97551
14 =>	Output Node 1	(target,output) =	0.00000,	0.04909

15 => Output Node 1 (target,output) = 0.00000, -0.10410
16*=> Output Node 1 (target,output) = 1.00000, -0.17639
17*=> Output Node 1 (target,output) = 0.00000, -0.15983
18*=> Output Node 1 (target,output) = 1.00000, -0.15983
19*=> Output Node 1 (target,output) = 0.00000, -0.17243
20*=> Output Node 1 (target,output) = 1.00000, -0.17243
21*=> Output Node 1 (target,output) = 0.00000, -0.18156
22*=> Output Node 1 (target,output) = 0.00000, -0.17253
23*=> Output Node 1 (target,output) = 0.00000, -0.18530
24*=> Output Node 1 (target,output) = 1.00000, -0.16109
25*=> Output Node 1 (target,output) = 1.00000, -0.15983
26*=> Output Node 1 (target,output) = 0.00000, -0.15983
27*=> Output Node 1 (target,output) = 0.00000, -0.18590
28*=> Output Node 1 (target,output) = 0.00000, 0.12131
29*=> Output Node 1 (target,output) = 0.00000, 0.89717
30*=> Output Node 1 (target,output) = 1.00000, -0.18702
31*=> Output Node 1 (target,output) = 0.00000, -0.10435
32*=> Output Node 1 (target,output) = 0.00000, 0.13847

B.3 Betweeness

Table B-3 Betweeness

betweeness	day 1	day 2	day 3	day 4	day 5	day 6	day 7	day 8	day 9	day 10	bias	target
M	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	1.000
s4831301026	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000
s4831501001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	1.000
s4831006079	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000
por	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	1.000
s4731501043	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000
s4831006027	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000
s4831301075	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.300	1.000	0.000
s4831501008	0.000	0.000	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	1.000	1.000
korkai	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	1.000
s4931402021	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000
s4931501006	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000
s4731501031	0.000	0.000	0.000	0.167	0.003	0.167	0.167	0.167	0.056	0.000	1.000	0.000
s4831501010	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.111	0.056	1.000	0.000
s4831601373	0.000	0.000	0.000	0.000	0.003	0.583	0.583	0.583	0.056	0.056	1.000	1.000
s4931501034	0.000	0.000	0.000	0.000	0.003	0.167	0.167	0.167	0.056	0.000	1.000	0.000
s4931501041	0.000	0.000	0.000	0.000	0.003	0.083	0.083	0.083	0.056	0.056	1.000	0.000

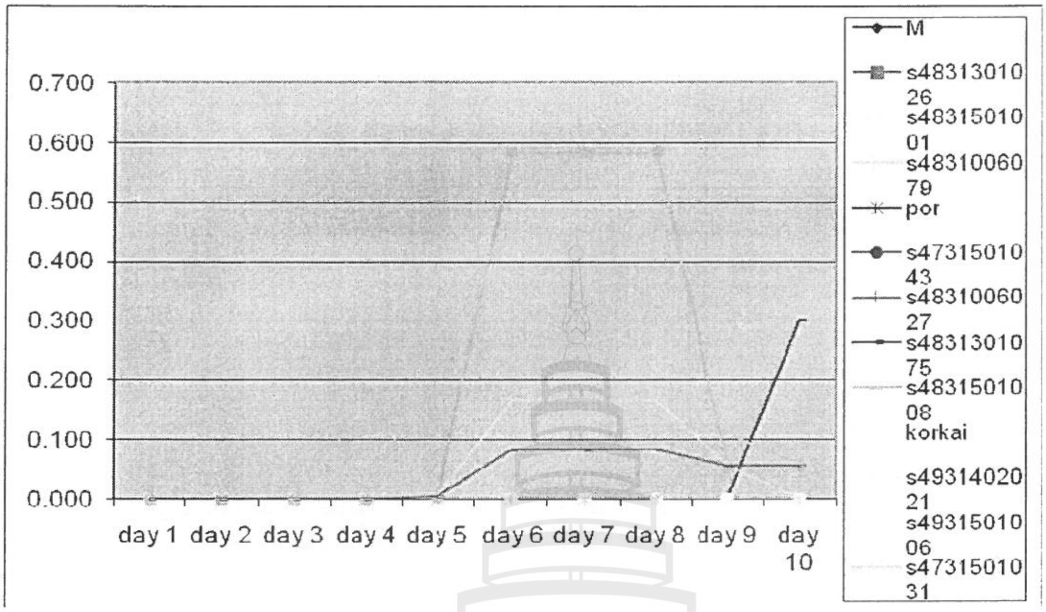

Figure B-6 Patterns of Betweeness

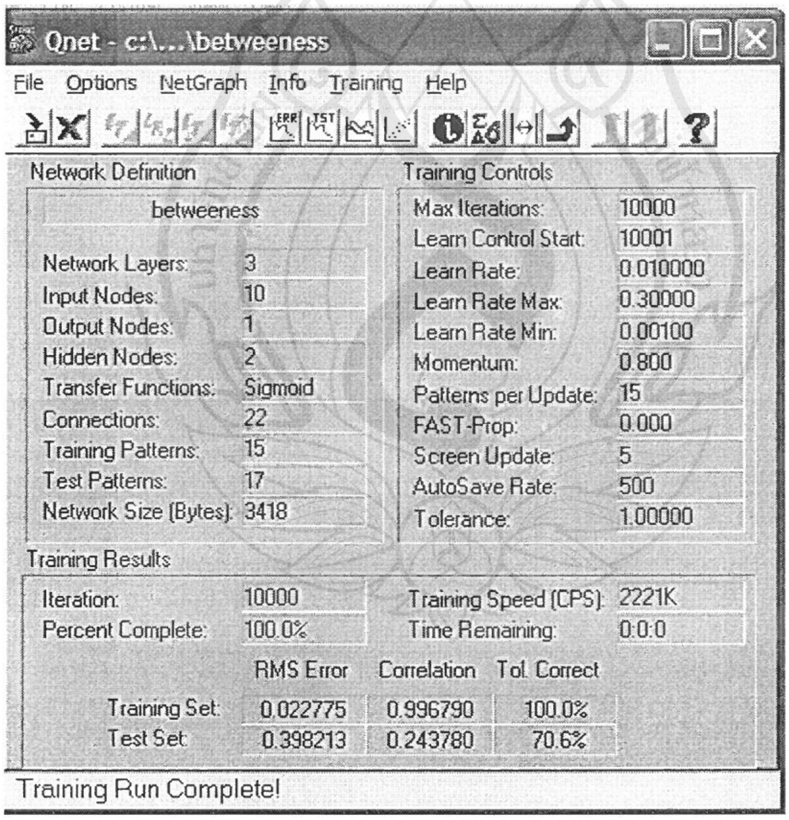

Figure B-7 The result of Betweeness

Targets and Network Outputs
Network Name: betweeness
Iterations: 10000

(Note: * = Test Pattern)

1 =>	Output Node 1	(target,output) =	0.00000,	-0.01696
2 =>	Output Node 1	(target,output) =	0.00000,	-0.01696
3 =>	Output Node 1	(target,output) =	1.00000,	0.97797
4 =>	Output Node 1	(target,output) =	0.00000,	0.05352
5 =>	Output Node 1	(target,output) =	0.00000,	-0.01696
6 =>	Output Node 1	(target,output) =	0.00000,	-0.02247
7 =>	Output Node 1	(target,output) =	1.00000,	0.96720
8 =>	Output Node 1	(target,output) =	0.00000,	-0.01696
9 =>	Output Node 1	(target,output) =	0.00000,	-0.01696
10 =>	Output Node 1	(target,output) =	0.00000,	-0.00084
11 =>	Output Node 1	(target,output) =	0.00000,	0.09412
12 =>	Output Node 1	(target,output) =	0.00000,	-0.01696
13 =>	Output Node 1	(target,output) =	0.00000,	-0.00846
14 =>	Output Node 1	(target,output) =	1.00000,	1.00204
15 =>	Output Node 1	(target,output) =	0.00000,	-0.01696
16*=>	Output Node 1	(target,output) =	1.00000,	-0.01696
17*=>	Output Node 1	(target,output) =	0.00000,	-0.01696
18*=>	Output Node 1	(target,output) =	1.00000,	-0.01696
19*=>	Output Node 1	(target,output) =	0.00000,	-0.01696
20*=>	Output Node 1	(target,output) =	1.00000,	-0.01696
21*=>	Output Node 1	(target,output) =	0.00000,	-0.01696
22*=>	Output Node 1	(target,output) =	0.00000,	-0.01696
23*=>	Output Node 1	(target,output) =	0.00000,	-0.09108
24*=>	Output Node 1	(target,output) =	1.00000,	-0.01522
25*=>	Output Node 1	(target,output) =	1.00000,	-0.01696
26*=>	Output Node 1	(target,output) =	0.00000,	-0.01696
27*=>	Output Node 1	(target,output) =	0.00000,	-0.01696
28*=>	Output Node 1	(target,output) =	0.00000,	0.08627
29*=>	Output Node 1	(target,output) =	0.00000,	0.01717
30*=>	Output Node 1	(target,output) =	1.00000,	0.44660
31*=>	Output Node 1	(target,output) =	0.00000,	0.09808
32*=>	Output Node 1	(target,output) =	0.00000,	0.02010

CURRICULUM VITAE

1. Name:

ดร. พรรณฤมล เต็มดี

Dr. Punnarumol Temdee

2. ID:

Personal ID: 3969900208435

Official ID: 49213048

3. Position and Affiliation:

Lecturer, School of Information Technology,

Mae Fah Luang University

Tel. 053-916757

Email: punnarumol@rocketmail.com

4. Education:

2006: Ph.D. in Computer Engineering, King Mongkut's University of Technology Thonburi (KMUTT), Bangkok, Thailand.

Dissertation Title: Of Collaborative Learning: An Approach for Emergent Leadership Roles Identification

1999: Master of Engineer, Electrical Engineering, KMUTT, Bangkok, Thailand.

Thesis Title: Face Recognition by using Fractal Geometry and Backpropagation Neural Network

1997: Bachelor of Engineer, Electronics and Telecommunication Engineering, KMUTT, Bangkok, Thailand.

Project Title: Accessing Control by Smart Card

5. Research Experience:

April 2003 – September 2004 :

Visiting Researcher: student agent developing on JADE, Digital Media in Education, University of Bremen, Germany

June 2002 – March 2003:

Research Assistant: agent developing for Social Network Analysis, Computer Engineering Department, KMUTT,

Bangkok, Thailand

July 2000 – June 2001:

Visiting Researcher: agent developing for Social Network Analyzing, Institute of Information Technology (IIT), The National Research Council of Canada (NRC), Ottawa, Canada.

6. Expert Area:

- Multi agent system
- Artificial Intelligence, Pattern Recognition
- Computer Supported Collaborative Learning
- Student and Team Modeling
- Content Management, Knowledge Sharing
- Social Network Analysis

7. Publications:

- Punnarumol Temdee, Bundit Thipakorn, Booncharoen Sirinaovakul and Heidi Schelhowe, "Of Collaborative Learning Team: An Approach for Emergent Leadership Roles Identification", Edutainment 2006, Hangzhou, China, April 16-19, 2006, pp. 745-754.

- Punnarumol Temdee, Bundit Thipakorn, Booncharoen Sirinaovakul and Heidi Schelhowe, "Of Collaborative Learning: An Approach for Emergent Leadership Roles Identification", IADIS International Conference Cognition and Exploratory Learning in Digital Age (CELDA2005), Porto, Portugal, Dec. 14-16, 2005, pp. 513-516.
- Punnarumol Temdee, Bundit Thipakorn, Booncharoen Sirinaovakul and Heidi Schelhowe, "Of Collaborative Learning: An Agent Based Approach for Social Network Analysis", World Conference on E-Learning in Corp., Govt., Health, & Higher Ed.(ELEARN2003), Phoenix, Arizona, USA, November 7-11, 2003, pp. 1786-1789.
- Punnarumol Temdee and Larry Korba, "Of Networks, Interactions and Agents: An Approach for Social Network Analysis", The Sixth International Conference on Computer Supported Cooperative Work in Design, London, Ontario, Canada, July 12-14, 2001, pp. 324-329.
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