OPINION MINING FOR ONLINE TEACHING EVALUATION

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วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิทยาการสารสนเทศดุษฎีบัณฑิต
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Suranaree University of Technology has approved this thesis submitted in fulfillment of the requirements for the Degree of Doctor of Information Science in Information Technology

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สมจิน เปียโคกสูง : การทำเหมืองความคิดเห็นสำหรับการประเมินการสอนออนไลน์ (OPINION MINING FOR ONLINE TEACHING EVALUATION) อาจารย์ที่ปรึกษา : ผู้ช่วยศาสตราจารย์ ดร.ธรา อั่งสกุล, 210 หน้า.

การวิจัยนี้มีวัตถุประสงค์เพื่อ 1) บ่งชี้องค์ประกอบของลักษณะการสอนที่ดี และ 2) ออกแบบและพัฒนากรอบการทำงานที่มีประสิทธิภาพเพื่อการวิเคราะห์ความคิดเห็นของนักศึกษาจากการประเมินการสอนออนไลน์จำแนกตามองค์ประกอบของลักษณะการสอนที่ดี โดยใช้เทคนิคทางสถิติและเครื่องจักรเรียนรู้ ในส่วนของการระบุถึงองค์ประกอบลักษณะการสอนที่ดีใช้แบบสอบถามในการสำรวจข้อมูลจากคณาจารย์ประจำ 97 คนและนักศึกษามหาวิทยาลัยเทคโนโลยีสุรนารี 474 คน วิเคราะห์ข้อมูลด้วยโมเดลสมการเชิงโครงสร้าง (SEM) ในการออกแบบและพัฒนากรอบการทำงานที่มีประสิทธิภาพเพื่อการวิเคราะห์ข้อความความคิดเห็นของนักศึกษา ข้อมูลที่นำมาทดลอง ได้แก่ ข้อความความคิดเห็นของนักศึกษาจำนวน 40,000 ข้อความจากระบบประเมินการสอนออนไลน์ ซึ่งได้มาโดยวิธีการสุ่มอย่างง่าย

ผลการวิจัยพบว่า

1. องค์ประกอบของลักษณะการสอนที่ดี ประกอบด้วย 6 องค์ประกอบและค่าน้ำหนักของแต่ละองค์ประกอบ ดังนี้ 1) องค์ความรู้ (2.55) 2) การเตรียมการสอน (2.19) 3) เทคนิคและกลวิธีการสอน (4.57) 4) การวัดและประเมินผล (2.01) 5) สื่อและอุปกรณ์การสอน (1.75) และ 6) บุคลิกลักษณะ (3.90) โดยมีค่าสถิติไคสแควร์เท่ากับ 27.77 องศาอิสระ 31 ความน่าจะเป็น 0.63 ค่าดัชนีระดับความกลมกลืน 0.99 ค่าดัชนีรากกำลังสองเฉลี่ย 0.019 ค่าดังกล่าว แสดงว่าองค์ประกอบที่นำเสนอสอดคล้องตามข้อมูลเชิงประจักษ์ที่รวบรวมจากอาจารย์และนักศึกษาได้เป็นอย่างดี

2. กรอบการทำงานเพื่อการวิเคราะห์ข้อความความคิดเห็น ประกอบด้วย 3 โมดูลหลัก ได้แก่ 1) เตรียมข้อมูลภาษาเบื้องต้น 2) วิเคราะห์ความคิดเห็น และ 3) การรวมกลุ่มและการทำให้มองเห็น ซึ่งระบบสามารถสกัดสารสนเทศที่สอดคล้องตามองค์ประกอบของลักษณะการสอนที่ดีและสามารถประมาณค่าประสิทธิภาพการสอนของอาจารย์ได้ โดยเทคนิคที่ให้ประสิทธิภาพสูงสุด คือ การใช้โครงข่ายประสาทเทียมหลายชั้นสำหรับการวิเคราะห์กระถดถอย มีระดับความสัมพันธ์เชิงลำดับโดยรวมในระดับสูงที่ 0.689 อย่างมีนัยสำคัญทางสถิติที่ 0.01 พิจารณาตามกลุ่มจำนวน

ความคิดเห็นต่ออาจารย์ พบว่า กลุ่มที่มีความคิดเห็นมากกว่าหรือเท่ากับ 107 ข้อความต่ออาจารย์ มีระดับความสัมพันธ์เชิงลำดับที่สูงถึง 0.777 เมื่อเพิ่มกลุ่มที่มีความคิดเห็นมากกว่าหรือเท่ากับ 39 ข้อความกลุ่มมากกว่าหรือเท่ากับ 15 ข้อความ กลุ่มมากกว่าหรือเท่ากับ 5 ข้อความ และ มากกว่าหรือเท่ากับ 1 ข้อความ มีระดับความสัมพันธ์เชิงลำดับ 0.722, 0.656, 0.690 และ 0.689 อย่างมีนัยสำคัญทางสถิติที่ 0.01 ตามลำดับ

สาขาวิชาเทคโนโลยีสารสนเทศ ลายมือชื่อนักศึกษา ____________________

ปีการศึกษา 2558 ลายมือชื่ออาจารย์ที่ปรึกษา ______________

SOMJIN PHIAKOKSONG : OPINION MINING FOR ONLINE TEACHING EVALUATION. THESIS ADVISOR : ASST. PROF. THARA ANGSKUN, Ph.D., 210 PP.

GOOD TEACHING CHARACTERISTICS/STUDENT FEEDBACK/ OPINION MINING

The purposes of this research were: 1) to identify the component of good teaching characteristics, and 2) design and develop an efficient framework for analysis the student feedback from online teaching evaluation according to the component of good teaching characteristics, by utilizing the statistical technique and machine learning technique. In section of identifying the component of good teaching characteristics. The questionnaire was used to survey data from 97 faculty and 474 students of Suranaree University of Technology (SUT). These data were analyzed with the Structural Equation Model (SEM) approach. In order to design and develop an efficient framework for analysis student feedback. The experimental dataset is 40,000 student feedbacks from online teaching evaluation system which obtained by simple random sampling technique.

The research findings are as follows:

1. The component of good teaching characteristics consists of 6 components with their factor loading as follows: 1) Knowledge (2.55) 2) Teaching preparation (2.19) 3) Teaching techniques and strategies (4.57) 4) Measurement and evaluation (2.01) 5) Teaching media and materials (1.75) and 6) Personality (3.90). It had a 27.77 of Chi-square where df = 31, p-value equal to 0.63, GFI was 0.99, and SRMR was

0.019. These statistical values indicated that the purpose components were corresponding with the empirical data that gather from SUT faculty and students.

2. A framework for analysis student feedbacks consists of 3 main modules including: 1) Linguistics Pre-processing 2) Opinion Analysis and 3) Aggregation and Visualization. This proposed framework can extracted information that corresponds with the component of good teaching characteristics, and also estimated their teaching performance score. The technique that provides highest performance was the Multi-Layer Perceptron for Regression. The overall performance was 0.689 of Spearman-Rho order ranking correlation with statistical significant at 0.01. Considering in the number of feedbacks per each faculty, the group which have feedback more than 107 per faculty obtained high level of ranking correlation ($r = 0.777$). Cumulative with the other groups ($\geq$ 39 feedbacks, $\geq$ 15 feedbacks, $\geq$ 5 feedbacks, and $\geq$ 1 feedback), they obtained the ranking correlation equal to 0.722, 0.656, 0.690 and 0.689 with statistical significant at 0.01, respectively.

School of Information Technology Student's Signature ___________________

Academic Year 2015 Advisor's Signature ___________________

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Somjin Phiakoksong

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CHAPTER 1

INTRODUCTION

1.1 Statement and Significance of Problem

Over the centuries, education plays a vital role as the foundation of society. The progressive society and wealthy economy are

A result of the good citizen which has the high quality of education. Education has ability to change and advance the society, contributing the growth of national income and individual learning (Varghes, 2007). In international communities there are established international organizations that promote the education as one of principle task to developed country e.g., United Nations Educational, Scientific, and Cultural Organization (UNESCO), Organization for Economic Co-operation and Development (OECD), etc.

Every countries concentrate on the importance of education to be an infrastructure for developing the country. Governments are responsible for enforcing the educational policy and established the educational institute from primary education to higher education. Educational institutes become the main source to provide education, accumulate and transfer knowledge, stimulate people to generate new ideas (Varghes, 2007), and cultivate ethics to people becoming the good citizen. Therefore, the quality of educational institute is an importance issue that should bring up to standard and acceptable by national and international people.

Several public and private educational institutes were established and operated complying with the government's education policy. All educational levels, especially, higher education is under the social pressure. The demand of educational stakeholders (e.g, students, parents, employees and public) is growing. They expect the educational institutes to provide the quality of teaching and learning process up to the standard and correspond with economic situation (Jallade, Radi and Cuenin, 2001; Hogg, R. and Hogg, M., 1995).

To meet these expectations, several higher education institutes are concerned to improve their education quality. In early 1970s, a unit called "Faculty development" is first established in USA. This unit focuses on developing teaching skills. The unit specializes in improving the teaching effectiveness of faculty members (Isil Kabakci and Odabasi, 2008). The American Association of Higher Education (AAHE) identifies the goal of Faculty development as follows; 1) providing teachers with training opportunities to achieve maximum effectiveness; 2) ensuring that employees develop their skills and capabilities to be able to work efficiently and respond rapidly to changes within their organizations; 3) improving performance of their present duties; 4) ensuring that the best use is made of the natural abilities and individual skills of all employees for the benefit of the organization and their career (Bokonjic, Ljuca and Steiner, 2009). To achieve these faculty development's goals, useful resource in regard to the quality of teaching is needed.

To develop quality of teaching, feedbacks from the educational stakeholder are a valuable resource that educational institute should not be ignored (Kannan and Bielikova, 2010). Several educational institutes usually use the questionnaire to survey information from stakeholders. Especially, surveying information from students who are direct stakeholder that affected by the different quality of educational institutes. In correspondence with Coyle and Powney (1990, quote in Powney and Hall, 1998), the student's feedback is an important component that occurs in a loop linking between teachings and learning as shown in Figure 1.1.

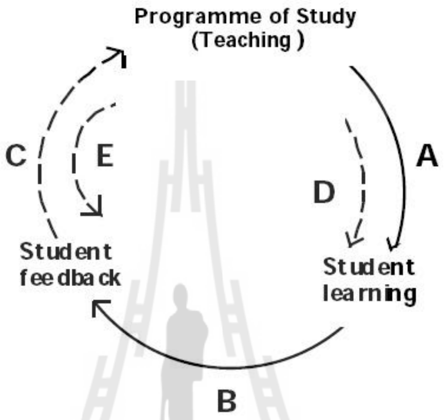


Figure 1.1 Closing the loop between teaching and student's feedback (Coyle and Powney, 1990, quote in Powney and Hall, 1998)

In recent years, to gather information from stakeholder, a popular tool called "Student Evaluations of Teaching (SET)" has been used in educational institute, especially, universities and colleges. SET is used to survey the opinion about the quality of classroom's teaching and learning processes from students who have enrolled in various subjects (Moss and Hendry, 2002). These educational institutes use the information of this evaluation to monitor quality of teaching and to help teachers improve their teaching effectiveness. The administrator also use these SET results as fundamental information for planning their administration policy such as promoting instructors, selecting teachers and assistant teachers for teaching awards, assigning teachers to courses, hiring new instructors, etc. (Badur and Mardikyan, 2011).

Generally, a SET is consists of a series of question items which presents in three basic types: 1) Close-ended question: it is a question form which fixed the choices of answer including: Multiple Choice Question (MCQ) and Rating Scale responses, 2) Open-ended question: it is a question form that allow students to response in free format of text paragraphs and 3) Combination of two mentioned types of question. SET are answered by students anonymously at the end of the semester without the faculty member's presence (Alhija and Fresko, 2009; Sproule, 2000).

Thanks to the advent of computer network technologies. The traditional paper-based surveying of SET is transformed into electronic-based surveying (also known as "Teaching Evaluation System") (Moss and Hendry, 2002). However, these electronic-based questionnaires still keep the traditional format similar to paper-based questionnaires. Most of the electronic-based questionnaire are appeared in the third forms which combining of close-ended and open-ended question.

Regarding close-ended question, Jordan (2011) described the characteristics of close-ended question as follows; 1) the answer of student seems to provide higher positive rating, 2) the data is excellent quantitative, but limit in details. It is not much helpful for institutional level evaluation apart from ranking, 3) the questions are vetted by administrators and faculty groups that influence what can and cannot be asked, and 4) these close-ended question are only created to present some aspects that the administrator or committees had paid attention. While, the open-ended question is the most important part which can give a clearer picture of what the students really feel or think. It is able to provide insight on how a course was conducted, what went well, and what could be improved. In addition, these open-ended question can reveal other perspectives which are not take into account by the close-ended question (Abd-Elrahman, Andreu and Abbott, 2010; Jordan, 2011).

As mentioned above, the characteristic of answer in closed-ended question is the structured data that provide the quantitative data which is easy to analyze and compare by statistical calculations. While the answer of open-ended question is student's opinion or attitude about teaching process which represented in free format of text paragraph.

Although, the student opinion is useful, unfortunately these student's opinions are usually ignored to take into analysis. Because of the characteristics of the open-end question's answer are unstructured data which is difficult to process with the simple statistical process (Reja, Manfreda, Hlebec and Vehovar, 2003; Jordan, 2011). Moreover, free format and vast amount of these data seem to be a problem for the administrators and faculties to spend time to analyze these unstructured data of student's opinion.

To overcome this problem, a process called "Opinion Mining (OM)" which gets the great interesting that can extract useful information from vast amount of stakeholder feedbacks. This process provides the benefit for human in aspects of decreasing the analyzing time and human's burden. Technically, this process is a cross-discipline field between Information Retrieval and Computational Linguistics (Bhuiyan, Xu and Josang, 2009). It aims on the automatic process that can analyze the opinion or attitude of an individual from text sentences, which represented in natural language. To the best of our knowledge, OM is often implemented in the business field. There are only few studies which applied OM in the education field.

This study aims to design and develop an efficient opinion mining framework to analyze Thai student feedback. The final results of this framework are knowledge that uses to indicate the strengths and weakness of individual teaching that correspond with good teaching characteristics.

1.2 The Objectives of Study

The objectives of this dissertation are as follows:

1. To identify the component of good teaching characteristics that corresponds with Thai educational context.

2. To design and develop an efficient opinion mining framework for analyzing student feedback from online teaching evaluation corresponds with good teaching characteristics.

1.3 Research question

1. What are the components of good teaching characteristic in Thai educational context?

2. What is the performance of opinion mining framework that can analyze Thai student feedbacks?

1.4 Hypothesis

1. The component of good teaching characteristics has the statistical indicator results higher than the standardized thresholds.

2. The proposed opinion mining framework can compute the entire opinion score from student feedback correctly with correlation greater than or equal 70% of ranking correlation.

1.5 Expected Results

1. Obtain the components of good teaching characteristics which correspond with Thai educational context.

2. Obtain an efficient opinion mining framework that can indicate the strength and weakness in teaching from Thai student feedback.

1.6 Scope of Study

This study aims to analyze Thai student's feedback sentences which respond in online teaching evaluation system of Suranaree University of Technology (SUT).

1.7 Definitions

1. **Online teaching evaluation system**:

It is an electronic system for student to evaluate teaching process. This system is used to survey information about the quality of teaching from the students of Suranaree University of Technology.

2. **Good teaching characteristics**:

List of teaching characteristics that the teacher and students of Suranaree University of Technology have identified that be the good characteristic of teaching. This list has been statistically verified that the characteristics are good teaching characteristics which correspond with Thai educational context.

3. **Opinion sentence**:

The feedback sentences that obtain from open-end questions answered in online teaching evaluation system. These sentences express the opinion or attitude of Thai students on the efficiency of teaching of their teacher in each course.

4. **Opinion mining**:

A field of data mining that combined the machine learning technique and natural language processing to analyze vast amounts of unstructured text data. The result of this process is the knowledge that corresponds with objective of the study.

5. **Feature words**:

The word that was extracted from student feedback sentence. These words identify the aspect of teaching characteristic of their teacher which corresponds with the good teaching characteristics.

6. **Opinion words**:

The word that was extracted from student feedback sentence. These words imply the attitude of student in teaching of their teacher in regarding to the good teaching characteristics.

7. **Good teaching knowledge**:

The opinion scores and the extracted phrases about teaching characteristics from opinion mining framework. The teacher can use these scores to indicate strength and weakness in their teaching performance that correspond with good teaching characteristics.

CHAPTER 2

LITERATURE REVIEW

To develop an efficient opinion mining framework for extraction knowledge from Thai student's feedbacks. The six major sections are studied and summarize. These sections consisting of, 1) Teaching factors and characteristics of good teaching, this section described about theoretical of teaching and previous studies that related with the characteristics or components of good teacher, 2) Thai language processing and application, this section contains the characteristics of Thai language and list of recently application that handle with Thai language, 3) Linguistic resources, described about the available lexicon which can utilize in Thai language mining process, and 4) Opinion mining is a section that describes general process of opinion mining, and also presented some efficient machine learning and statistical technique that used in this work. The last two sections are the related work and summary of overall reviewed. These six major sections are described as follows:

2.1 Teaching factors and characteristics of good teaching

2.1.1 Teaching and learning process

2.1.2 Literature review of teaching factors and characteristics of good teaching

2.1.3 Structural Equation Modeling

2.2 Thai language processing and application

2.2.1 Fundamental of Natural Language Processing

2.2.2 Thai language and processing

1) Characteristics of Thai language

2) Applications for Thai language processing

- Word segmentation application

- Part-Of-Speech tagging application

2.3 Linguistic resources

2.3.1 Lexicon and Thai dictionary

1) WordNet and SentiWordNet

2) LEXiTRON

2.3.2 String similarity approaches

1) Text similarity

2) Semantics similarity

2.4 Opinion Mining

2.4.1 Overview of Opinion Mining

2.4.2 Machine Learning and Statistical approaches for Opinion Mining

2.5 Related work

2.5.1 Opinion Mining in Non-Educational field

2.5.2 Opinion Mining in Education field

2.5.3 Opinion Mining with Thai language

2.6 Summary

2.1 Teaching factors and characteristics of good teaching

Teaching is an important part of education process that aims to change the student behavior follow the learning objectives. Lacking of improving teaching process would affect the quality of education. Teaching is a process that depends on several factors such as content, teaching activity, teaching experience of teacher in order to encourage the student to learn, etc. In order to understand the good teaching characteristics, there is some background knowledge that related with teaching process as described below:

2.1.1 Teaching and learning process

Over the last two decade, there are several definitions about teaching and learning defined by the educationists and philosophers.

Hills (1982 quote in Jaitiang, 2003) defined that "Teaching is process that provides the education to the students which arise on the interaction between teacher and their students".

Moore (1992 quote in Jaitiang, 2003) defined that "Teaching is behavior of any person that attempts to help and support other persons to enhance themselves".

Boonchuvong (1990 quote in Jaitiang, 2003) defined meaning of teaching is "The organization of experiments that suitable for the students to learn or change their behavior in better aspect".

Jaitiang (2003) defined that "Teaching is interaction process between teacher and learners in order to change their learners' behavior that correspond with the learning objective".

Good (1959 quote in Nakhon Ratchasima Teacher College, 1993) defined the definition of teaching in two aspects that are 1) "Teaching" is providing of education to children in the school and 2) "Teaching" is preparing the activities, materials and giving the consulting about learning process to children.

Gagne *et al*. (1992 quote in Srisai, 2003) state that "Teaching is a group of events or situation that facilitates the learners to achieve the learning objectives".

As mentioned above, the definition of "Teaching" can be defined as "The suitable process that provide by teacher to support or facilitate their students in order to enhance themselves".

Normally, "Teaching and learning" is process that the learners had learning together with any activity and under the suggestion of teacher. Learners would receive the experience that establishes knowledge, understanding, ability, skills and good attitudes to enhance themselves (Nakhon Ratchasima Teacher College, 1993). In teaching and learning process, there are several things that teacher should concentrate as follows:

1) *Teaching*: Effort of any person that would manage the learning activity to make a person or group of persons obtains the learning process.

2) *Purpose* or *Objective of teaching*: the goal of learning process that make any learner enhance themselves in the aspect of human body, emotional, social and intelligence. This purpose would help the learner have ability to solve problem in real life.

3) *Principle to teaching methodology*: Knowledge and technique to teach the learner to learn by doing, experiment, research, and problem solving by themselves.

4) *Important components that make teaching successful*: They consist of Teacher (or Faculty), Contents, Learner and Understanding of the teacher about learning process.

- Teacher (or Faculty): Ability and personality of teacher that influences to the learning of learner. Teacher should enhance themselves personality to support the learning of learner. Selecting of teaching techniques and adopt of their teaching process with various methods to make attention to learner.

- Contents: the suitable of contents for learning process is an important component. Systematic of content management would support the learner to learn faster and easier. Teacher should concern about the different structure and nature of contents in each group of experiments that provide to the student.

- Learner: the quality of learner is the outcome of teaching. Each learner has difference of ability to learn. Providing the educational to different persons, teacher should prepare the teaching process for individual and a group of persons.

- Understanding of the teacher about learning process: Learning process is the process which makes change on student's behavior. In aspect of teaching, learning is the ability of learner to learn and adopt any experience to solve the problem. Learning is a direct affect from any action of learner in the class, while, the teacher is a facilitator to encourage the educational atmosphere in the class.

5) *Having evaluation process*: Teaching should have monitoring the progress of learner. Evaluation process helps the teacher to assess the successful of teaching and learning process.

As mentioned above, the quality of teaching and learning process is involved with the teacher. Teacher is the major component that influences and linkages between the learning experiment and student. The teacher who has the professional skill of teaching will help students to achieve their objective learning.

2.1.2 Literature review of Teaching factors and characteristics of good teaching

"Teacher" (or "Faculty" in higher educational context) is an important component in teaching and learning process. Therefore, the basic knowledge on the teaching and learning process is the basic requirement of every teacher. Knowing about the characteristic and factor of good teaching would be guideline for the teacher to achieve the high quality of teaching in practice.

Educational researchers had studies and proposed the characteristic and factor of good teaching under the difference context of educational institutes. Summary of previous studies on good teaching characteristics are shown in Table 2.1.

Table 2.1 Summary of previous studies on the characteristics of good teaching

Order	***Researchers***	***Number of characteristics***	***Component of good teaching***					
			Knowledge	*Preparation*	*Teaching technique*	*Assessment*	*Materials*	*Personality*
1	Cooper and Foy (1967)	43			•		•	•
2	Eble (1971)	5	•	•	•	•		•
3	Sheffield (1974)	10	•	•	•			•
4	Ebro (1977)	9	•		•			•
5	Lewis (1982)	8	•		•			•
6	Landbeck (1997)	3			•			•
7	Smith (1980)	8			•	•		
8	Jaitiang (2003: In Thai)	13		•	•			

Table 2.1 Summary of previous studies on the characteristics of good teaching (continued)

Order	***Researchers***	***Number of characteristics***	***Component of good teaching***					
			Knowledge	*Preparation*	*Teaching technique*	*Assessment*	*Materials*	*Personality*
9	Thompson *et al.*, (2004)	12		•				•
10	STOW on the world primary school (2005)	11	•	•		•		•
11	Gurney (2007)	5	•		•	•		•
12	Jahangiri and Mucciolo (2008)	21	•	•	•		•	•
13	College of Agricultural and Life Sciences, University of Florida (2009)	5	•		•		•	•
14	Biostatistics, Johns Hopkins University (2009)	39		•	•	•	•	•
15	Aregbeyen (2010)	17						•
16	Al-hebaishi (2010)	4	•	•	•	•		•

The previous works have shown that there are many items of good teaching characteristics which depend on the different context of studies. However, these characteristics items can be roughly grouped into six components: knowledge, preparation, teaching technique, assessment, materials, and personality.

1) Knowledge: Teacher has enough content knowledge for teaching and answering the questions of students.

2) Preparation: Teacher has good teaching preparation (contents, process, and materials) before actual teaching.

3) Teaching technique: Teacher has methods and techniques to transfer his/her knowledge to the students and also has the ability to control his/her students in the classroom.

4) Assessment: Teacher has fair judgment and validity of the assessment process to indicate achievements of students.

5) Material: Teacher utilizes suitable teaching materials and has teaching assistants to support his/her teaching process.

6) Personality: Teacher has good personal behavior and good human relations.

Additionally, most of the previous works indicated that the teaching techniques and personality components are the most important components of good teaching characteristics.

Knowing of good the teaching characteristics would be benefit for the teacher in order to improve their teaching style. However, these teaching characteristics should be adopted in appropriate manner with the educational institute context.

2.1.3 Structural Equation Modeling

Structural Equation modeling (SEM) is a research approach used in many academic disciplines, including information systems and marketing (Jacobson *et al.*, 2009). SEM is a general term that describes a large number of statistical models which are used to test and validate substantive theories with empirical data (Lei and Wu, 2007). This technique combines a measurement model (or Confirmatory Factor Analysis (CFA)) and structural model into a simultaneous statistical test. The patterns of relationships between these latent variables are constructed based on the study of educational theory. SEM is a statistical method to model the relationships among multiple predictor and criterion variables (Hoe, 2008).

Lei and Wu (2007) explained that SEM involves several statistical techniques e.g., Factor analysis, Path analysis, and Regression. These statistics are used to evaluate two models: a measurement model and a path model.

1) Measurement model: is a measuring of latent variables originated from psychometric theories. Unobserved latent variables cannot be measured directly but are indicated by responses to a number of observable variables (indicators). In social sciences, latent constructs are a set of indirect observation variables (latent variables) such as intelligence or reading ability. These variables and their relationships are often gauged by responses to a battery of items that are designed to tap those constructs. Responses of a study participant to those items are supposed to reflect where the participant stands on the latent variable. Statistical techniques such as factor analysis, exploratory or confirmatory, have been widely used to extract the number of latent constructs underlying the observed responses and to evaluate the adequacy of each item or variables as indicators for the latent constructs they are supposed to measure.

2) Path model (also known as "Structural Model"): is a statistical approach which is an extension of multiple regressions. It involves various multiple regression models that are estimated simultaneously. This provides a more effective and direct way of mediation modeling, indirect effects, and other complex relationships among variables. Path analysis can be considered a special case of SEM in which structural relations among observed (vs. latent) variables are modeled. Structural relations are hypotheses about directional influences or causal relations of multiple variables (e.g., how the independent variables affect dependent variables). Hence, path analysis (and also the more generalized; SEM) is sometimes referred as causal modeling. Because analyzing interrelations among variables is a major part of SEM and these interrelations are hypothesized to generate specific observed covariance (or correlation) patterns among the variables, SEM is also sometimes called covariance structure analysis. The relationship between Measurement model and Path model can be depicted as shown in Figure 2.1.

In general, every SEM analysis goes through the steps of model specification, data collection, model estimation, model evaluation, and (possibly) model modification. Issues pertaining to each of these steps are discussed below.

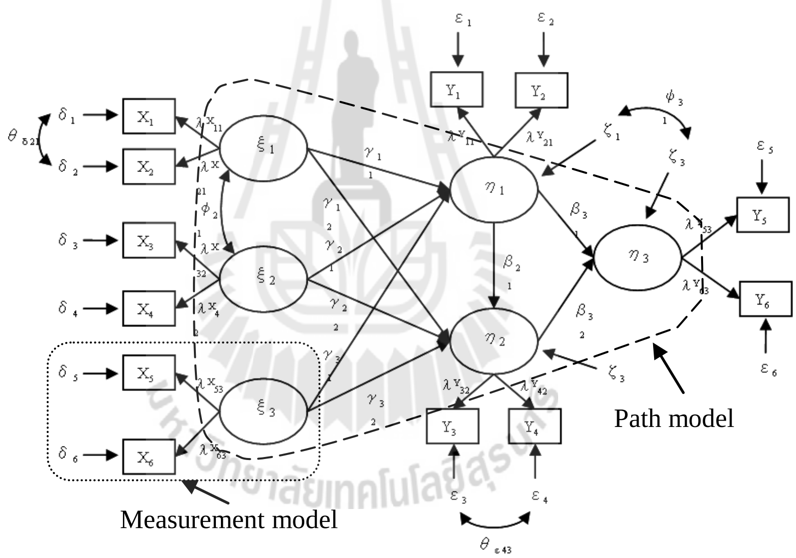


Figure 2.1 Relationship between Measurement model and Path model

1) Model Specification: a sound model is theoretical based. Theory is based on findings in the literature, knowledge in the field, or one’s educated guesses, from which causes and effects among variables within the theory are specified. Models are often easily conceptualized and communicated in graphical forms. In these graphical forms, a directional arrow (→) is universally used to indicate a hypothesized causal direction. The variables to which arrows are pointing are commonly termed endogenous variables (or dependent variables) and the variables having no arrows pointing to them are called exogenous variables (or independent variables). Unexplained covariance among variables is indicated by curved arrows (↔). Observed variables are commonly enclosed in rectangular boxes and latent constructs are enclosed in circular or elliptical shapes.

2) Data Characteristics: like conventional statistical techniques, score reliability and validity should be considered in selecting measurement instruments for the constructs of interest and sample size needs to be determined preferably based on power considerations. The sample size required to provide unbiased parameter estimates and accurate model fit information for SEM models depends on model characteristics (e.g., model size) as well as score characteristics of measured variables (e.g., score scale and distribution).

3) Model Estimation: a properly specified structural Equation model often has some fixed parameters and some free parameters to be estimated from the data. As an illustration in Figure 2.1, it shows the diagram of a conceptual model which consist of parameter γ and β. That is, when the parameter value of a visible path is fixed to a constant, the parameter is not estimated from the data. Free parameters are estimated through iterative procedures to minimize a certain discrepancy or fit function between the observed covariance matrix (data) and the model-implied covariance matrix (model). Definitions of the discrepancy function depend on specific methods used to estimate the model parameters. A commonly used discrepancy function is derived from the maximum likelihood method.

4) Model Evaluation: once model parameters have been estimated, one would like to make a dichotomous decision, either to retain or reject the hypothesized model. Essentially, a statistical hypothesis-testing problem with the null hypothesis being that the model under consideration fits the data. The overall model goodness of fit is reflected by the magnitude of discrepancy between the sample covariance matrix and the covariance matrix implied by the model with the parameter estimation (a.k.a. the minimum of the fit function or F_{min}). Most measurement of overall model goodness of fit are functionally related to F_{min}. The model test statistic $(N–1)\ F_{min}$, where N is the sample size, has a chi-square distribution (i.e., it is a chi-square test) when the model is correctly specified and can be used to test the null hypothesis that the model fits the data.

To obtain good teaching characteristics, the good teaching characteristics items that proposed in previous studies are summarized as a questionnaire. Social research process is used to survey information from Thai instructors and Thai students. The good teaching characteristics that appropriate with Thai educational context are revealed. These good teaching characteristics are used to be initial structure of knowledge base of the proposed system.

2.2 Thai language processing and application

To develop a system that deals with human language, the basic knowledge about processing of natural language are required. This section presents the fundamental of Natural Language Processing (NLP), the characteristics of Thai language processing, and the linguistic resources for Thai language.

2.2.1 Fundamental of Natural Language Processing

Natural language processing (NLP) is a widely field that aims to studying on linguistic processing. The definition of NLP is defined by several scholars as follows: Hayes and Carbonell (1983) states that “Natural language processing is the formulation and investigation of computationally effective mechanisms for communication through natural language”. Liddy (1998: p. 137) states that “Natural language processing is a set of computational techniques for analyzing and representing naturally occurring texts at one or more levels of linguistic analysis for the purpose of achieving human-like language processing for a range of tasks or applications”. Dale, Moisl and Somers (2000: p. v) states in “Handbook of Natural Language Processing” that “NLP concern with the design and implementation of effective natural language input and output components for computational systems”.

According to these definitions, NLP is a process or a technique to analyze linguistic structure, extracting meaningful information from natural language or input/product of natural language that human-like. Presently, NLP was implemented as underneath technique of several tasks that support in building an automatic system, e.g., Information Retrieval (IR) (Paul and Lisa, 1988: p. 85; Nihalani, Silakari, and Motwani, 2011), Information Extraction (IE), Machine Translation (MT) (Hutchins and Somers, 1992: p. 2) and Text Summarization (TS) (Das and Martins, 2007).

To develop the application that could extract or understand the meaning of text or spoken language. NLP defines the level of linguistics analysis in six levels as shown in Figure 2.2.

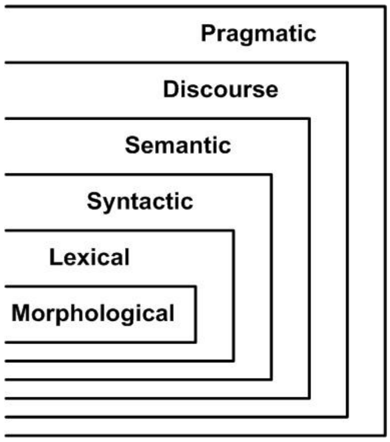


Figure 2.2 Level of linguistics analysis (Liddy, 1998: p. 138)

2.1) Morphological level: this level has to deal with the smallest grammatical units of language called "*morphemes*". This is the smallest meaningful pieces of words. For example, the morpheme "*ed*" at the end of a verb tells that the action took place in the past. Additionally, simple things like adding the morpheme "un" to "lawfully" drastically change the meaning of the word.

2.2) Lexical level: this level is concerned with linguistic processing at the word level and includes such processing including Part-Of-Speech tagging. When humans hear or read a sentence, they determine that a word can function both as a verb and as a noun, either a verb or a noun in that particular sentence. Knowing about Part-Of-Speech of word is useful for word sense disambiguation.

2.3) Syntactic level: this level is concerned the order and arrangement of words within a sentence convey meaning. For example, the sentence "*อธิบาย/แล้ว/เข้าใจ/ไม่ค่อย/งง*" contains the same words as "*ไม่ค่อย/เข้าใจ/อธิบาย/แล้ว/งง*" but the simple ordering of those words conveys a world of difference in meaning.

2.4) Semantic level: this level is concerned with understanding the meaning of words within context i.e., humans are able to unambiguously understand words when they hear them or read them in a sentence even though many words have multiple meanings. For example, in the English language, the most commonly occurring verbs each have eleven meanings (or senses) and the most frequently used nouns have nine senses, but humans can correctly select the one sense or meaning that is intended by the author or speaker.

2.5) Discourse level: this level is concerned with units of text larger than a sentence. Discourse is a newer area of linguistic applications, having begun as an area of linguistic study in the 1970s. Discourse linguistics is concerned with the linguistic features that enable humans. For example, to understand the eighth sentence in a paragraph partly because of the meaning they extracted from the first to seventh sentences. Discourse is also concerned with utilizing the fact that texts of a particular type (a.k.a. "genre") have a predicable informational structure and that humans use this structure to infer meaning that is not explicitly conveyed at any of the other levels in the model.

2.6) Pragmatic level: this level is concerned with the knowledge and meaning that we assign to text using our world knowledge. For example, the phrase "Third World Countries" does not just mean those three words to a reader. Pragmatic knowledge brings in a lot of other understanding, such as which are the Third World Countries and the general socioeconomic conditions in these countries.

2.2.2 Thai language processing

NLP were studied mostly on the European languages which roots of word are from Latin such as English, Dutch, French, Spanish, etc. Research on Asian language has thrived in the past few years. There is a workshop initiated in 2001 called "The Asian Language Resources Workshops". Since 2006, several conferences including COLING/ACL published papers that deal with Bengali, Filipina, Hindi, Marathi, Thai, Urdu, and Vietnamese (Huang, Tokunaga and Lee, 2006: pp. 209-210). Thai is a language which is used in some countries of South-East Asia, especially Thailand. Characteristic of Thai language had studied and described in the following section.

1) Characteristics of Thai language

Thai language is an attractive language which has been studied by several researchers. Palingoon (2011: pp. 171-172) has studied and summarized the characteristics and properties of Thai language as 29 items that some are differ from English language as shown in Table 2.2.

Table 2.2 Characteristics and properties of Thai language

No.	Characteristics and properties
1.	Isolating/Monosyllabic language (คำพยางค์เดียว/ภาษาคำโดด)
2.	Tone (เสียงวรรณยุกต์)
3.	Short and Long vowel (สระสั้น-ยาว)
4.	Final consonant (พยัญชนะท้ายคำ)
5.	Stress (การลงน้ำหนักเสียง)
6.	Intonation (ทำนองเสียง)
7.	Word order (การเรียงลำดับคำ) - Subject+Verb+Object : SVO (ประธาน+กริยา+กรรม) - Topic+comment (หัวข้อ+ส่วนขยาย)
8.	Homonym, Homophone, Synonym (คำพ้อง เสียง รูป ความหมาย)
9.	Word formation (การสร้างคำหลากหลาย)
10.	Rhyming words (คำสัมผัสคล้องจอง)
11.	Classification (คำลักษณะนาม)
12.	Special mark for mute consonant (ตัวการันต์/ทัณฑฆาต)
13.	Reduplication (การซ้ำ)

Table 2.2 Characteristics and properties of Thai language (continued)

No.	Characteristics and properties
14.	Register (ระดับการใช้ภาษา)
15.	Particle/ ending word (คำลงท้าย)
16.	Reduced word (การละคำ)
17.	Serial verb (กริยาเรียง)
18.	Syllable structure (โครงสร้างพยางค์: C(C) V(V1-5) C)
19.	Discourse-oriented language (ภาษาอิงข้อความ)
20.	Word space (การเว้นวรรคระหว่างคำ)
21.	Space functions (หน้าที่ของการเว้นวรรค)
22.	Capital letter (ไม่มีอักษรตัวใหญ่)
23.	Vowel position (ตำแหน่งของรูปสระ)
24.	Collocation (คำปรากฏร่วม)
25.	Polysemy (คำหลายหน้าที่และคำหลายความหมาย)
26.	Interrogative sentence (ประโยคคำถามมีลักษณะเฉพาะ)
27.	Left to Right writing (การเขียนเรียงจากซ้ายไปขวา)
28.	Variation of tones to letters (การผันอักษร)
29.	Diphthong (คำควบกล้ำ)

According to mentioned characteristics of Thai language, Thai researchers were studied and identified the obstacle of NLP with Thai language in four major issues as follows (Sornlertlamvanich *et al*., 2000; Jirawan and Asanee, 2006; Sukhum, Nitsuwat and Haruechaiyasak, 2011).

1) Thai language does not have the punctuation marks, such as space or full stop to identify word or sentence boundary and also does not have the capital letter.

2) The ambiguous of word meaning when appears in different position in sentence or in difference context.

3) There are special word genres, such as Name Entity, Transliteration word or Phrase from word compounding.

4) Flexible of grammatical structural, some component of sentence (subject or object) can be omitted.

Furthermore, Palingoon (2011: pp. 179-185) described the effect of "*Electronics grammar*" which is an evolution of written style. This is an obstacle characteristic of language processing e.g., the words which written follow speaking sound, repeating of vowel or characters, using the group of symbols to represent their feeling called "emotion". These special characteristics of written forms usually found in modern communication system e.g., Short-Messaging-Service (SMS), Web Board, Chats room, Web Blog or Social media (e.g., Facebook, Twitter, etc.).

According to the characteristics of language and written style as mentioned above, there are three principal problems of NLP with Thai language are defined, that are 1) Word segmentation, 2) Sentence segmentation, and 3) Lexicon ambiguity (Modhiran *et. al.*, 2005).

2) Applications for Thai language processing

To overcome the problems as stated above, there are several applications were developed to process Thai language as follows.

2.1) Word Segmentation Application

Text segmentation or term tokenization is one of the fundamental tasks in natural language processing (NLP). Most NLP applications require input text to be tokenized into individual terms or words before being processed further. For example, in machine translation, text must first be tokenized into a series of terms before it can be further analyzed and translated into another language. For information retrieval systems, in which the inputs are text documents and text queries, text is first tokenized into individual terms. The processed terms are then organized into an inverted file index data structure for fast retrieval. In speech synthesis applications, the tokenized terms are segmented further into syllables, which are then mapped into phoneme units. Like Chinese, Japanese, and Korean, the Thai written language is unsegmented, i.e., it is written continuously without the use of word delimiters (Haruechaiyasak, Kongyoung and Dailey, 2008). Presently, there are several application were develop to tokenize Thai language such as SWATH, LibThai, KUcut, LexTo, TLexs etc.

- **SWATH**: Smart Word Analysis for Thai (SWATH) is a general-purpose utility for analyzing Thai word boundaries and inserting predefined word delimiter codes. The original version was released by Charoenpornsawat (1999). It can be used to preprocess Thai LaTeX documents. The longest matching and maximal matching algorithms are used as segmentation algorithm. It also included the bigram part of speech tagging based on Orchid corpora resource. The latest version contains 23,944 words in internal dictionary. These words are extracted from Thai common dictionary and manually added by maintainer.

- **LibThai**: an open source libraries for Thai language support which developed by Karoonboonyanan *et al.* (2001). It performed under Unix/Linux platform. This library consists of character support, character properties, string manipulators, string collation, input/output method and word segmenting. The word segmenting feature of LibThai was implemented the maximal matching algorithm and selected the minimal number of words for speed optimization in practice. It contains

23,563 words from Thai dictionary of the Royal Institute of Thailand. The words in LibThai dictionary are manually added by maintainer.

- KUcut: KU wordcut is a Thai word segmentation program which proposed in 2003 (Sudprasert and Kawtrakul, 2003). It was continue developed with Python language and disseminated under the license of Kasetsart University, NAiST Research Laboratory. It differs from SWATH in aspects of using the novel unsupervised machine learning algorithm as a main process to segment unknown words.

- LexTo: Thai Lexeme Tokenizer (NECTEC, 2004; 2006) is a word segmentation program which obtains the winner award for Enhancing the Standard of Thai Language Processing (BEST 2009). It was developed by National Electronics and Computer Technology Center (NECTEC), Thailand. LexTo is an open source software which released under the license of GNU Lesser General Public License (LGPL). It uses the longest matching algorithm with the dictionary base. The initial dictionary of LexTo is derived from the LEXiTRON which consist 42,221 words.

- TLexs: Thai Lexeme Analyser (Haruechaiyasak and Kongyoung, 2009; NECTEC, 2009) is a word segmentation application which proposed in the InterBEST 2009 Thai Word Segmentation workshop**.** It is a machine learning system which used the Conditional Random Fields (CRFs) as segmentation algorithm.

Both of the LexTo and TLexs were developed by NECTEC, which available online via Sansarn website (NECTEC, 2004). The difference between both is “LexTo” is dictionary based that allows users to add specific words to the dictionary. This implies that LexTo is dynamic application. While “TLexs” uses Conditional Random Field (CRF) as method to segment words. It was already modeled from a five million word corpus (Thumrongluck and Mongkolnavin, 2011). This implies that TLexs restricts to add up new specific words into it.

2.2) Part-Of-Speech tagging application

Part-Of-Speech (POS) tagging is usually considered as front-end preparation process. In the past two decades, most POS tagging systems were based on a sequential classification approach, decomposing a sequence labeling task into a series of classification subtasks. The state of the art of tagging was achieved by virtue of well-developed machine learning method e.g., the Maximum Entropy model, the Support Vector Machine, etc. (Chen and Kit, 2011). Several Part-Of-Speech tagging application were released for English language processing. To the best our knowledge, there are few resources and applications developed to process Thai language. The Part-Of-Speech tagset and tagging applications are described as follows.

2.2.1) Thai linguistic corpus and Part-Of-Speech tagset

The existing Thai corpus is divided into two types; Speech and Text corpus which developed by many Thai Universities. Originally, the goal of the text corpus is used only inside their own laboratory. From surveying of Kawtrakul *et al.*, (2002), there are some of Thai text corpus were developed, that are the NAiST corpus (Kawtrakul *et al.*, 1995) and ORCHID corpus (Sornlertlamvanich, Charoenporn and Isahara, 1997).

- **NAiST corpus**: this corpus introduced in 1996. The primary aim is to collect document from magazines for training and testing program in Written Production Assistance system (Kawtrakul *et al.*, 1995). This corpus is continued collecting and released under the license of NAiST Research Laboratory, Kasetsart University, Thailand. NAiST corpus consists of 60,511,974 words with the 49 Part-Of-Speech tagset (NAiST, n.d.). These Part-Of-Speech tagset is shows in Table 2.3.

Table 2.3 NAiST corpus tagset

No.	POS	Description	Example Words
		NOUN	
1.	npn	Proper noun	น้ำดอกไม้ อัจฉรา
2.	nnum	Cardinal number	พัน หมื่น แสน ล้าน etc.
3.	norm	Ordinal Number Marker	ที่
4.	nlab	Label noun	1 2 ก ข
5.	ncn	Common noun	ช้าง ม้า
6.	nct	Collective noun	ฝูง พวก พรรค
7.	ntit	Title noun	นาย นาง นางสาว
		PRONOUN	
8.	pper	Personal pronoun	เขา คุณ ท่าน ฉัน
9.	pdem	Demonstrative pronoun	นี้ นั้น นั่น
10.	pind	Indefinite pronoun	ใคร ๆ ผู้ใด ต่าง บ้าง
11.	ppos	Possessive pronoun	ของคุณ ของเรา
12.	prfx	Reflexive pronoun	เอง ตัวเอง
13.	prec	Reciprocal pronoun	กัน
14.	prel	Relative pronoun	ที่ ซึ่ง อัน
15.	pint	Interrogative pronoun	ทำไม อะไร อย่างไร
		VERB	
16.	vi	Intransitive verb	เดิน นั่ง ซึม กดดัน กระจาย
17.	vt	Transitive verb	กรุณา กลัว กวนใจ
18.	vcau	Causative verb	ให้ ทำให้

Table 2.3 NAiST corpus tagset (continued)

No.	POS	Description	Example Words
19.	vcs	Complementary state verb	เป็น อยู่ คือ กล่าวคือ
20.	vex	Existential verb	มี
21.	prev	Pre-verb	จะ ยัง คง กำลัง ย่อม
22.	vpost	Post-verb	ไป มา ขึ้น ลง
23.	honm	Honorific marker	พระ ทรง พระราช
		DETERMINER	
24.	det	Determiner	นี้ นั้น
25.	indet	Indefinite determiner	ใด อื่น อย่างไร
		ADJECTIVE	
26.	adj	Adjective	ขยัน กำยำ กิตติมศักดิ์
		ADVERB	
27.	adv	Adverb	กลางคัน กว่า แรก สุดท้าย ก่อน หลัง
28.	advm1	Adverb marker1	อย่าง
29.	advm2	Adverb marker2	เป็น
30.	advm3	Adverb marker3	โดย
31.	advm4	Adverb marker4	สัก
32.	advm5	Adverb marker5	ตาม
		CLASSIFIER	
33.	cl	Classifier	เชือก เซนติเมตร ทาง ประเทศ ชิ้น etc.
		CONJUNCTION	
34.	conj	Conjunction	และ ในที่นี้
35.	conjd	Double conjunction	ทั้ง...และ ไม่...ก็ ทั้ง....ทั้ง
36.	conjncl	Noun clause conjunction	ว่า ให้ ได้แก่ เช่น
		PREPOSITION	
37.	prep	Preposition	กับ โดย เมื่อ ตรง
38.	prepc	Co-preposition	ระหว่าง...กับ ตั้งแต่...จนถึง
		INTERJECTION	
39.	int	Interjection	เอ๊ะ อ๋อ อุ๊ย ว้าย ดอก ดูกร

Table 2.3 NAiST corpus tagset (continued)

No.	POS	Description	Example Words
		PREFIX	
40.	pref1	Prefix1	การ ความ
41.	pref2	Prefix2	ผู้ นัก
42.	pref3	Prefix3	ชาว
		PARTICLE	
43.	aff	Affirmative	ค่ะ ครับ จ้า ครับผม
44.	part	Particle	นัก นั่นเอง เป็นต้น
		NAGATIVE	
45.	neg	Negative	ไม่ มิ ไร้
		PUNCTUATION	
46.	punc	Punctuation	. - , ‘
		IDIOM	
48.	idm	Idiom	รักวัวให้ผูก รักลูกให้ตี
		PASSIVE VOICE MARKER	
48.	psm	Passive voice marker	ถูก โดน
		SYMBOL	
49.	sym	Symbol	ฯลฯ ฯ % ๆ

- ORCHID corpus: ORCHID is the code name of a project for building Thai POS tagged corpus which initiated by a group of researchers from Communications Research Laboratory (CRL) of Japan and National Electronics and Computer Technology Center (NECTEC) of Thailand. This project started in April 1996. The purpose of this project is to prepare Thai language corpus for linguistic research, especially, developing applications for processing Thai language under the computational environment. The structure of the ORCHID Corpus consists of 2 types of text, that are *the information line*, a line beginning with a “%” character, and *the numbering line*, a line beginning with a “#” character. The Part-Of-Speech label of each word is in the form of “/[POS]”. The ORCHID corpus used the 47 subcategories as the POS tagset. These tagset are shown in Table 2.4.

Table 2.4 ORCHID corpus tagset

No.	POS	Description	Example Words
1.	NPRP	Proper noun	วินโดวส์ 95 โคโรน่า โค้ก พระอาทิตย์
2.	NCNM	Cardinal number	หนึ่ง สอง สาม 1 2 3
3.	NONM	Ordinal number	ที่หนึ่ง ที่สอง ที่สาม ที่1 ที่2 ที่3
4.	NLBL	Label noun	1 2 3 4 ก ข a b
5.	NCMN	Common noun	หนังสือ อาหาร อาคาร คน
6.	NTTL	Title noun	ดร. พลเอก
7.	PPRS	Personal pronoun	คุณ เขา ฉัน
8.	PDMN	Demonstrative pronoun	นี่ นั่น ที่นั่น ที่นี่
9.	PNTR	Interrogative pronoun	ใคร อะไร อย่างไร
10.	PREL	Relative pronoun	ที่ ซึ่ง อัน ผู้
11.	VACT	Active verb	ทำงาน ร้องเพลง กิน
12.	VSTA	Stative verb	เห็น รู้ คือ
13.	VATT	Attributive verb	อ้วน ดี สวย
14.	XVBM	Pre-verb auxiliary, before negator “ไม่”	เกิด เกือบ กำลัง
15.	XVAM	Pre-verb auxiliary, after negator “ไม่”	ค่อย น่า ได้
16.	XVMM	Pre-verb, before or after negator “ไม่”	ควร เคย ต้อง
17.	XVBB	Pre-verb auxiliary, in imperative mood	กรุณา จง เชิญ อย่า ห้าม
18.	XVAE	Post-verb auxiliary	ไป มา ขึ้น
19.	DDAN	Definite determiner, after noun without classifier in between	นี่ นั่น โน่น ทั้งหมด
20.	DDAC	Definite determiner, allowing classifier in between	นี้ นั้น โน้น นู้น
21.	DDBQ	Definite determiner, between noun and classifier or preceding quantitative expression	ทั้ง อีก เพียง

Table 2.4 ORCHID corpus tagset (continued)

No.	POS	Description	Example Words
22.	DDAQ	Definite determiner, following quantitative expression	พอดี ถ้วน
23.	DIAC	Indefinite determiner, following noun; allowing classifier in between	ไหน อื่น ต่างๆ
24.	DIBQ	Indefinite determiner, between noun and classifier or preceding quantitative expression	บาง ประมาณ เกือบ
25.	DIAQ	Indefinite determiner, following quantitative expression	กว่า เศษ
26.	DCNM	Determiner, cardinal number expression	หนึ่งคน เสือ 2 ตัว
27.	DONM	Determiner, ordinal number expression	ที่หนึ่ง ที่สอง ที่สุดท้าย
28.	ADVN	Adverb with normal form	เก่ง เร็ว ช้า สม่ำเสมอ
29.	ADVI	Adverb with iterative form	เร็ว ๆ เสมอ ๆ ช้า ๆ
30.	ADVP	Adverb with prefixed form	โดยเร็ว
31.	ADVS	Sentential adverb	โดยปกติ ธรรมดา
32.	CNIT	Unit classifier	ตัว คน เล่ม
33.	CLTV	Collective classifier	คู่ กลุ่ม ฝูง เชิง ทาง ด้าน แบบ รุ่น
34.	CMTR	Measurement classifier	กิโลกรัม แก้ว ชั่วโมง
35.	CFQC	Frequency classifier	ครั้ง เที่ยว
36.	CVBL	Verbal classifier	ม้วน มัด
37.	JCRG	Coordinating conjunction	และ หรือ แต่
38.	JCMP	Comparative conjunction	กว่า เหมือนกับ เท่ากับ
39.	JSBR	Subordinating conjunction	เพราะว่า เนื่องจาก ที่ แม้ว่า ถ้า
40.	RPRE	Preposition	จาก ละ ของ ใต้ บน
41.	INT	Interjection	โอ้ย โอ้ เออ เอ๋ อ๋อ
42.	FIXN	Nominal prefix	การทำงาน ความสนุกสนาน
43.	FIXV	Adverbial prefix	อย่างเร็ว
44.	EAFF	Ending for affirmative sentence	จ๊ะ จ้ะ ค่ะ ครับ นะ น่า เถอะ
45.	EITT	Ending for interrogative sentence	หรือ เหรอ ไหม มั้ย
46.	NEG	Negator	ไม่ มิได้ ไม่ได้ มิ
47.	PUNC	Punctuation	เครื่องหมายต่าง ๆ เช่น (,), “, ,, ;

Both of the NAiST corpus and ORCHID corpus were widely used as principal corpus for NLP researchers to develop a Part-Of-Speech software package or Web service that handle with Thai language. However, there are only few software that could deals with Part-Of-Speech tagging for Thai language are available, e.g., SWATH, KUcut, Jitar (with NAiST model), OpenNLP. The description of this software is as follows.

As mentioned in section of Word Segmentation Application, the SWATH and KUcut were released as standalone applications; however, there are some attempts to implement them as service via Internet system.

- **Thaisemantics.org**: Poltree and Saikaew (2012) create a website, namely, "Thaisemantics.org" which provided a service to segment Thai sentences into word and tag their Part-Of-Speech. The proposed services are developed base on the SWATH and ORCHID tagset.

- **KU Wordcut Demo**: Sudprasert and Kawtrakul (2003) were proposed a website which implemented the KUcut as underneath process. The website called the "KU Wordcut Demo". The demonstration website was provided NLP functions as same as Thaisemantics.org website; however, it was developed as web application which limits the maximum input is 500 characters.

Beside, two mentioned websites; there are some standalone applications for Part-Of-Speech tagging with Thai language named "Jitar (with NAiST model)" and "OpenNLP".

- **Jitar (with NAiST model)**: Jitar is a generally Part-Of-Speech tagger which is original developed by Daniël de Kok (2010). It is a Java application based on a trigram Hidden Markov Model (HMM) algorithm. Recently, Vee Satayamas, a Thai researcher of NAiST Research Laboratory has released the Thai Part-Of-Speech model for Jitar. It can access via NAiST website (NAiST, 2011). As same as the KU Wordcut Demo, Jitar with Thai language processing was modeled based on the NAiST corpus.

- Apache OpenNLP: “The Apache Software Foundation” developed a Natural Language Processing library called “OpenNLP” (Apache Software Foundation, 2010). This software library is a machine learning based toolkit. It supports most common NLP tasks, such as tokenization, sentence segmentation, Part-Of-Speech tagging, etc. It also supports various European languages. To tag the Part-Of-Speech for Thai language, the language model was trained and available for OpenNLP version 1.4, which can access via sourceforge.net website. The OpenNLP language model is based on ORCHID corpus.

As mentioned before, the word segmentation and Part-Of-Speech tagging are basic requirement of any application that handle with Natural Language Processing. In this work, the LexTo is selected as our word segmentation tool because of its flexibility in recognizing new words that are not included in the dictionary. In context of student feedbacks where spoken language is used more often than written one, LexTo appears to be a more appropriate tool. In regarding to the Part-Of-Speech tagging application, Zeng et al. (2013) presented an experiment about performance of Jitar and Apache OpenNLP. This experiment revealed that Jitar given a little bit higher of accuracies than Apache OpenNLP. In practice, Apache OpenNLP provided the Application Programming Interface (API) with complete of their manual and also can use it as Command Line Interface (CLI). These characteristics provided benefit for the developer in order to include it as part of a developed system. While the Jitar only provided the Command Line Interface (CLI) and lack of their examples to used it. Per above reasons, the Apache OpenNLP is selected as Part-Of-Speech tagging in this work.

2.3 Linguistic resources and dictionary

Linguistic resources and dictionary are very important to Information Retrieval and Natural Language Processing fields. There are several work used these linguistic resources in aspect of, referring the meaning of word, finding and computing of word similarity, and also used as pre-defined categories to classify document contents. The famous general purposed linguistic resource is “WordNet” (Miller, 1995). It was invented in English language. There are extended version of WordNet in various languages e.g., Spanish, Italian, German, French, and Asian language called “AsianWordNet” (Sornlertlamvanich *et al.*, 2009). There is an extension of WordNet which provide the benefit for opinion mining tasks, called “SentiWordNet” (Esuli and Sebastiani, 2006). Besides, there are the other effort to build the linguistic resource for opinion mining tasks e.g., Bing Liu's Opinion Lexicon, MPQA Subjectivity Lexicon, Harvard General Inquirer, LIWC, SenticNet, etc. (Potts, 2011, Cambria and Hussain, 2012).

2.3.1 Lexicon and Thai dictionary

1) WordNet and SentiWordNet

1.1) WordNet: WordNet is a famous linguistic resource (a.k.a. “Princeton WordNet (PWN)”). At initial stage, it was developed as part of a project began in 1985 with a group of psychologists and linguists under the direction of

George A. Miller at Princeton University's Cognitive Science Library. PWN is an English linguistic resource which consists of four types of Part-Of-Speech that are Nouns (n), Verbs (v), Adjectives (a), and Adverbs (r). Vocabularies are organized into the sets of synonyms which represented of lexicalized concept and semantic relations link of these synonym sets (Miller, 1995).

The main relation among words in WordNet is synonymy (such as, the words “shut” and “close” or “car” and “automobile”). Synonyms words that denote the same concept are interchangeable in many contexts (as illustrated in Figure 2.3). These synonyms words are grouped into unordered sets with synsets ID. Additionally, a synset contains a brief definition called “gloss”. Gloss is one or more short sentences illustrate the use of these synset members. Several distinct meanings of word forms are represented in many distinct synsets. This network structure of words in WordNet is made it useful for using in Natural Language Processing and computational linguistics.

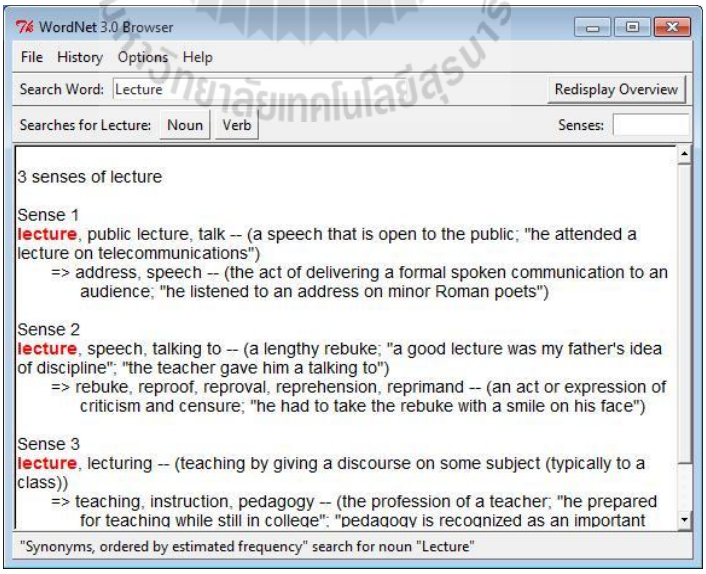


Figure 2.3 WordNet interface (Synonymy representation)

1.2) SentiWordNet: a linguistics resource which was developed based on terminology of WordNet, called "SentiWordNet" (Esuli and Sebastiani, 2006). This linguistics resource has a specified purpose to support the opinion mining task. This resource used semi-supervised learning approach to estimate opinion score of each terminology. The feature set for classifiers obtain from Term Frequency-Inverse Document Frequency (TF-IDF) and Cosine normalized weighting. The supervised learning algorithms (Rocchio and SVMs) are used to generate several semi-independent classifiers. Initializing with a small hand-labeled set (seed set), this automatic process are generates more labeled data with their opinion score. It uses WordNet lexical relationships to expand both "Positive" and "Negative" sets of terms. Terminologies of SentiWordNet and opinion score are stored in a plain text file. An excerpt of SentiWordNet file structure is shown in Table 2.5.

Table 2.5 An excerpt of SentiWordNet files structure

POS	ID	PosScore	NegScore	SynsetTerms	Gloss
a	00001740	0.125	0.000	able#1	(usually followed by `to') having the necessary means or skill or know-how or …
a	00002098	0.000	0.750	unable#1	(usually followed by `to') not having the necessary means …
…	…	…	…	…	…
n	00604811	0.000	0.000	teachership#1	the position of teacher
n	00604910	0.000	0.250	thaneship#1	the position of thane
…	…	…	…	…	…
v	02768874	0.375	0.125	glow#3 burn#2	shine intensely, as if with …
v	02769077	0.000	0.625	gutter#1	burn unsteadily, feebly, …
…	…	…	…	…	…

According to SentiWordnet files structure, these terms score can used in several style (Kreutzer and Witte, 2013). The six common ways to use these score are, 1) Sum up all scores, 2) Average all scores, 3) Sum up only for adjectives, 4) Average only for adjectives, 5) Average of all non-zero scores, and 6) Majority vote.

Although, there are general purposed linguistic resources available to access, however, those linguistic resources were developed base on European language. To develop a system that handles with Thai language processing, Thai dictionary is another important linguistic resource that should be concerned. Several existing of Thai dictionary is available and it also provides services both in online and offline e.g., LEXiTRON, LongDo Dictionary, the Royal Institute Dictionary and SEAlang library, etc. (Charoenporn *et al.*, 2003, Metamedia Technology, 2003, TICFIA Program, 2005, The Royal Institute, n.d.). LEXiTRON is a famous Thai linguistic dictionary that many researchers are referencing.

2) LEXiTRON

2.1) LEXiTRON: (Charoenporn *et al.*, 2003) is the first Thai-English corpus-based dictionary which is a project of Human Language Technology Laboratory of NECTEC. LEXiTRON was started in 1994. The structure of LEXiTRON is defined by a set of sample sentences and usages. In addition to their basic information, it provides Part-Of-Speech, classifier, verb pattern, synonym, antonym, and pronunciation. It was aimed to be a dictionary for writing. Most of the lexicons are originated from the dictionary developed for using with the Machine Translation project (the research and development of Multi-lingual Machine Translation System for Asian countries, 1987-1997). These information and word entry are suitable for both human and machine use. The first version of LEXiTRON was launched in 1996 as a CD-ROM dictionary for human use. Recently, after a concentrated revision, the second version was released under the open source concept for the contents. It is available in both stand-alone and on-line versions at NECTEC website (NECTEC, 2003). An example screenshot is shown in Figure 2.4.

Figure 2.4 LEXiTRON Dictionary interface

2.3.2 String similarity approaches

Gomaa and Fahmy (2013) had studied and categorized several similarity algorithms that related with text processing. Those algorithms were roughly separated into two groups including: 1) Text similarity and 2) Semantic similarity.

1) Text similarity

In text similarity, there are several algorithm were proposed e.g., Longest Common Substring (LCS), Levenshtein, Jaro, Jaro-Winkler, etc. These algorithms are "Character-based". Another type of text similarity is "Terms-based" e.g., Block distance, Cosine similarity, Dice's coefficient, Jaccard similarity, Overlap coefficient, etc. Details of some algorithms were presented as follows:

1.1) Jaro similarity: The Jaro algorithm is commonly used for name matching in data linkage systems. It is suitable and provides good performance for short text length. It account for insertion, deletion and transposition. The algorithm calculates the number *c* of common characters (agreeing characters that are within half the length of longer string) and the number of transpositions *t*. A similarity measure is calculated as Equation (2.1).

$$sim_{jaro}(s1, s2) = \frac{1}{3}\left(\frac{c}{|s1|} + \frac{c}{|s2|} + \frac{c-t}{c}\right) \quad (2.1)$$

1.2) Jaro-Winkler similarity: Base on the Jaro algorithm, W.E. Winkler improves performance of the traditional Jaro algorithm by applying ideas from empirical studies. The empirical studies revealed that there are fewer errors typically occur at the beginning of texts data. The Winkler increases the Jaro similarity measure for agreeing initial characters (up to four). It is calculated as Equation (2.2).

$$sim_{wink}(s1, s2) = sim_{jaro}(s1, s2) + \frac{p}{10}(1.0 - sim_{jaro}(s1, s2)) \quad (2.2)$$

With *p* being the number of agreeing characters at the beginning of two strings, where $p = \max(p_0, 4)$. For example: "peter" and "petra" have p=3, while, "peter" and "peter pan" have p=4.

1.3) Jaccard similarity: The Jaccard is a simple similarity method which computed the number of shared term over the number of all unique terms in both strings. Although, it was categorize into Term-based similarity, however, it can perform in level of *n*-sequence characters (a.k.a. *n*-grams). A similarity measure is calculated as Equation (2.3).

$$sim_{jaccard}(s1, s2) = 1 - \frac{p}{p+q+r} \tag{2.3}$$

Where p is number of term co-occurrence for both *s1* and *s2*. *q* is number of term that only occur in *s1*. *r* is number of term that only occur in *s2*.

2) Semantic similarity

In semantic similarity, Gomaa and Fahmy (2013) categorized similarity approaches into three types including: 1) Corpus-base similarity, 2) Knowledge-based similarity, and 3) Hybrid similarity. The first one is "Corpus-base similarity" which using complicated computation with large linguistic corpus to extract similarity score. There are several famous approach in this type e.g., Hyperspace Analogue to Language (HAL), Latent Semantic Analysis (LSA), Pointwise Mutual Information (PMI), Normalized Google Distance (NGD), etc. The second type of semantic similarity is "Knowledge-based similarity". This type requires a well structure of linguistic relationship to identify the closer of word meaning. The last one is "Hybrid similarity" which applies several approaches as described above to identify the semantic similarity of word.

Semantic computation based on WordNet is a type of Knowledge-based similarity. WordNet is a famous linguistics resource which several researchers utilized to compute semantic similarity of word. Semantics similarity techniques on WordNet can be categorized into four main groups (Varelas *et al.*, 2005) that are: 1) *Edge Counting Methods*: Measuring the similarity between two terms (concepts) as a function of the length of the path linking the terms and the position of the terms in the taxonomy, 2) *Information Content Methods*: Measuring the difference in information content of the two terms as a function of their probability of term occurrence in a corpus, 3) *Feature Based Methods*: Measuring the similarity between two terms as a function of their properties (e.g., their definitions or "glosses" in WordNet) or based on their relationships to other similar terms in the taxonomy, and 4) *Hybrid Methods*: This method combines several method of the previous groups. Term similarity is computed by matching synonyms, term neighborhoods, and term features. The popular methods of semantics similarity are described as follows:

2.1) Hirst–St-Onge: In 1998, Hirst and St-Onge proposed a semantic measurement. This is a measuring of semantic relatedness that two lexicalized concepts are semantically close, if their WordNet synsets are connected by a path that is not too long and does not change direction too often. The strength of the relationship is given by:

$$Sim_{HS}(c1,c2) = C - len(c_1,c_2) - k \times turns(c_1,c_2) \qquad (2.4)$$

Where C and k are constants (in practice, they used C = 8 and k = 1), and $turns(c_1,c_2)$ is the number of times the path between c_1 and c_2 changes direction. if no such path exists, $Sim_{HS}(c1, c2)$ is zero and the synsets are deemed unrelated.

2.2) Leacock–Chodorow: Leacock and Chodorow proposed a technique which rely on the length *len(c1, c2)* of the shortest path between two synsets for their measure of similarity. However, they limit on *IS-A* links and scale the path length by the overall depth *D* of the taxonomy. The similarity is given by:

$$sim_{LC}(c1,c2) = -\log\left(\frac{len(c1,c2)}{2D}\right) \quad (2.5)$$

2.3) Resnik: Resnik's approach is the first technique that bring ontology and corpus together. The idea of this technique is the similarity between a pair of concepts may be judged by "the extent to which they share information". Resnik defined the similarity between two concepts lexicalized in WordNet to be the information content of their lowest super-ordinate, *lso(c1, c2)*:. The similarity is given by:

$$sim_{res}(c1,c2) = -\log p(lso(c1,c2)) \quad (2.6)$$

Where *p(c)* is the probability of encountering an instance of a synset *c* in some specific corpus.

2.4) Jiang–Conrath: Jiang and Conrath's approach is an information content. However, they used the conditional probability of encountering an instance of a child-synset given an instance of a parent synset. Thus the information content of the two nodes is the most specific and plays a part. Notice that this formula measures semantic distance in the inverse of similarity. The similarity is given by:

$$Sim_{JC}(c1,c2) = 2\log(p(lso(c1,c2))) - (\log(p(c1)) + \log(p(c2))) \quad (2.7)$$

2.5) Lin: Lin's approach is similarity measure approach which follows the Jiang and Conrath theory. But, there is different fashion form of Sim_{JC}.

$$Sim_{lin}(c1,c2) = \frac{2 \times \log p(lso(c1,c2))}{\log p(c1) + \log p(c2)} \quad (2.8)$$

Recently, another technique of semantics similarity is proposed. This technique was proposed by Kamps *et al.* (2004).

2.6) Kamps: It implements the idea of famous psychological theory, called "the Charles Osgood's theory of semantic differentiation" with WordNet. They used semantic differential technique with the several pairs of bipolar words to scale the responses of subjects to words, short phrases, or texts. An example of bipolar words such as "active/passive", "good/bad", "optimistic/pessimistic", "positive/negative", "strong/weak", "serious/humorous", "ugly/beautiful", etc. This technique defined a function to measure the relative distance of a word to the two reference words, called "the evaluative factor (EVA)". For example, measuring of word *w* is having semantic closest with any words between "good" and "bad": can be defined are shown in Equation 2.9.

$$EVA(w) = \frac{d(w,bad) - d(w,good)}{d(good,bad)} \qquad (2.9)$$

Where *d* is the distance between two words which obtain by used semantic similarity approach as mentioned above. However, the boundary positions of words on the opposite site are not entirely justified. Using the geometry of triangle rule, the EVA function is redefined as Equation 2.10.

$$EVA_1(w) = \frac{(d(w,bad) - d(w,good)) \times ((d(w,bad) + d(w,good))}{d^2(bad,good)} \qquad (2.10)$$

In addition, there are other factors could be used, e.g., "the potency factor (POT)" and "the activity factor (ACT)". These factors used same equation with the difference types of pair of word references.

According to those semantics similarity approaches as mentioned above, the semantic similarity based on WordNet resource is an attractive approach to use in the development of an efficient opinion mining framework that can handle with Thai student's feedback. Moreover, the LEXiTRON, SentiWordNet and Machine Learning technique would be collaborate with WordNet to extract useful knowledge from student feedback to indicate teaching performance of teacher.

2.3.3 Association Measurement

Extraction of collocation from a corpus is a well-known problem in the field of natural language processing. It is typically carried out by employing some kind of a statistical measure that indicates whether or not two words occur together more often than by chance (Petrovic *et al.*, 2006). There are three algorithms that most widely used in extraction task as follows:

1) Pointwise Mutual Information (PMI): It is a measure that comes from the field of information theory. It measures the amount of the occurrence of one word from given information of the other word as Equation 2.11.

$$PMI(x,y) = \log_2 \frac{P(xy)}{P(x)P(y)} \tag{2.11}$$

Where x and y are words and $P(x)$, $P(y)$, $P(xy)$ are probability of occurrence of words x, y, and digram xy.

2) Chi-square test (χ^2): It emerges from the fields of statistics which deal with hypothesis testing. The hypothesis is accept "*null-hypotesis*" if "word x and y occur together by chance"). It defined as Equation 2.12.

$$\chi^2 = \sum_{i,j} \frac{\left(O_{ij} - E_{ij}\right)^2}{E_{ij}} \tag{2.12}$$

Where O_{ij} and E_{ij} are observed and expected frequencies in a contingency table.

3) The Log-Likelihood ratio (LL): It is a statistical test based on the likelihood ratio, which expresses how many times more likely the data are under one model than the other. Similarly Chi-square test, data are presented in contingency table. It defined as Equation 2.13.

$$G^2 = \sum_{i,j} O_{ij} \, log \, \frac{O_{ij}}{E_{ij}} \tag{2.13}$$

2.4 Opinion Mining

2.4.1 Overview of Opinion Mining

A popular field of data mining that deals with the human attitude and their expression is “Opinion Mining (OM)” (a.k.a. “Sentiment Analysis”). OM is interdisciplinary between Information Retrieval (IR) and Natural Language Processing (NLP). The aim of OM is an attempt to take advantage from vast amounts of user’s feedback by analysis and extracts with the sophisticated process and presents the formal knowledge. Several researchers reviewed main processes and also classified OM in several groups of characteristics e.g.; Bhuiyan, Xu and Josang (2009); Lee, D., Jeong and Lee, S. (2008); Abbasi, Chen and Salem (2008); Tsytsarau and Palpanas (2012). The overview of Opinion Mining can be depicted as Figure 2.5.

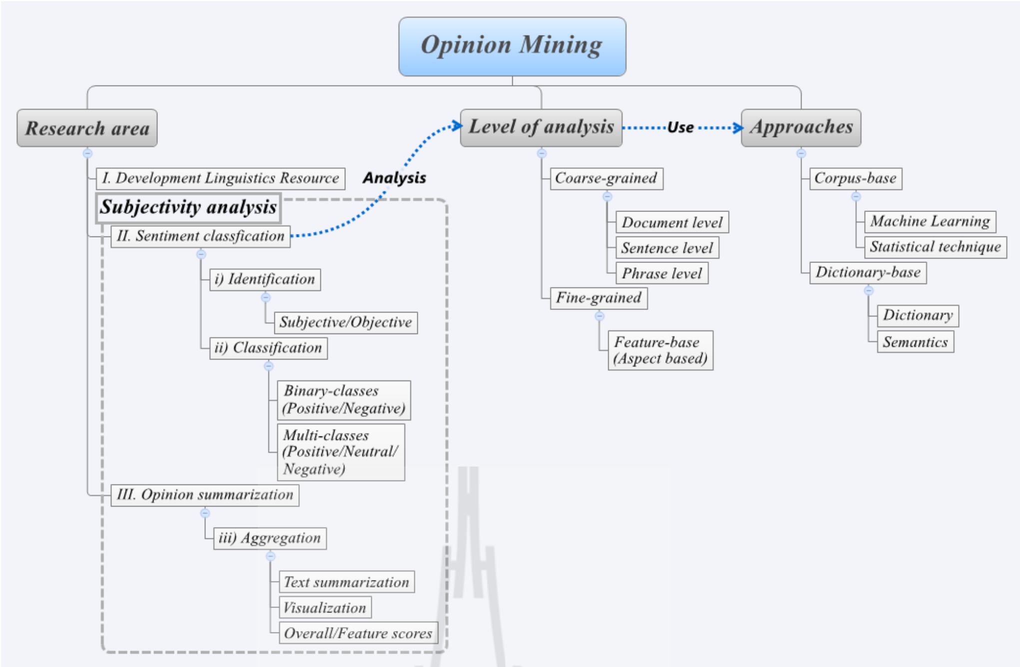


Figure 2.5 Overview of Opinion Mining

According to studying of Lee *et al*. (2008), OM research can be divided into three major research areas, including:

I. Development of linguistic resource.

II. Sentiment classification.

III. Opinion summarization.

In the development of linguistic resource areas, researcher emphasizes to construct linguistic resource for describing how authors express inter-subjective and ideological position. This area involves with linguistics theory such as Appraisal theory (Martin and White, 2005; Whitelaw, Garg and Argamon, 2005), Rhetorical structure theory (Heerschop, Goossen and Hogenboom, 2011) and computational linguistics. The result of this area is a lexicon that can be used as linguistics resource for the two remaining areas.

The last two areas of OM research are “Sentiment classification” and “Opinion summarization”. They are much overlapping of process and results (They can be called “Subjectivity Analysis”). This subjectivity analysis composed of three steps: i) identification, ii) classification and iii) aggregation. Identification and classification steps are involved with sentiment classification process. The result of these steps is producing sentiment values for texts paragraph. The identification step is a task to identify text paragraph or sentence into factual (Objective) or opinion (Subjective) texts. The classification step is to locate the position of texts on two polarities (binary categorization) such as “positive/negative”, “good/bad”, or classification on multi-classes categorization such as “positive/negative/neutral” (a.k.a. “discrete categorization”). Furthermore, this step measured the numeral rates value of opinion on each polar called “strength of polarity”. Esuli and Sebastiani (2005, 2006) defined the steps of sentiment classification as three specific subtasks that are 1) *Determining subjectivity*: Deciding whether a piece of text is factual or subjective (i.e. expresses an opinion about a particular topic), 2) *Determining polarity*: Deciding whether the expressed sentiment of a subjective piece of text is positive or negative, and 3) *Determining strength of polarity*: Grading the intensity of the expressed sentiment in a subjective piece of text. The first task of these steps can be considered as the identification step; while the two remain tasks are the classification steps.

Besides the step in sentiment classification, there is the last step of opinion summarization that is the aggregation step. This step involved in aggregate of sentiments scores (strength of polarity) from previous steps and presents them as textual summarization, overall scores, feature scores, or visualizes them as graphs or charts, etc. Overall, these steps are mostly utilized several sophisticated approach that related with statistical and mining techniques, machine learning or artificial intelligence (especially, involved with linguistics computational).

Considering of “Level of Analysis”, Bhuiyan et al. (2009) had studied and proposed the taxonomy of OM which represented as a hierarchy structure. Bhuiyan’s taxonomy divided OM into three sub-categories based on level of analysis including: document level, sentence level and feature-based level. The process of analysis is corresponding with the step in sentiment classification area.

Document level is classifying the overall sentiments expressed by the authors of the entire document text (can be considered as text paragraph). The purpose of this level is to determine whether the document is positive, negative or neural about a certain object. The sentence level is subtle level that performs in two steps: i) Identify each sentence as subjective or objective and ii) Classify and determine their sentiment (positive, negative or neutral) whether it is a subjective sentence. Furthermore, it is possible to analyze more subtle in phrase level (Wilson, Wiebe and Hoffmann, 2005). The phrase level is related with noun/verb phrase of sentences that is the source of opinion on object. The document and sentence level always has roughness analyze (a.k.a. “Coarse-grained analysis”) (Clayton *et al.*, 2011). Recently, there is a special case of OM, named, “Feature-based level”. It is categorized as “Fine-grained analysis” which is more detailed of analysis on feature of the interesting object. Feature-based level comprise of three tasks: (i) Extract object feature that are commented (ii) Determine their sentiment and (iii) Group feature synonyms and produce a summary (Hu and Liu, 2004; Liu, 2011). The analysis process of feature-based level is similar with general OM analysis process. However, there is some difference in the aspect of this level considered and analyzed each feature of an object as an independent object. The feature-based level is useful for supporting the decision of customer who concerns on some features of an object. In fact, basic process of analysis in feature-based level utilizes the coarse-grained analysis.

Considering of "Approaches", Tsytsarau and Palpanas (2012) summarized approaches of OM analysis into four groups. They are 1) Machine learning, 2) Dictionary, 3) Statistical, and 4) Semantic approaches. The machine learning approach is a sophisticated solution that had been most frequently exploited in the classification problem. Normally, this approach comprises of two-steps: (i) learn the model from a training data, and (ii) classify the unseen data based on the trained model. The dictionary approach relies on a pre-built dictionary that contains several vocabularies and their meanings. The dictionary approach can also combine with machine learning methods in order to analyze the opinion. The statistical approach used the mathematical and statistical method as computational model. This approach requires the large linguistics corpus. Frequency of word occurrence is used to identify polarities of words. The semantic approach based on formal structure and annotated dictionary. This approach use the relative shortest distance of "synonym" relation to identify polarities of words. In addition, these approaches can be categorized into two groups based on their resource used, that are corpus-based and dictionary-based groups. The corpus-based group used unstructured data to find co-occurrence patterns of words to determine the sentiment of words or phrases. The dictionary-based group used synonyms and antonyms in structured data to determine word sentiments (Bhuiyan *et al.*, 2009). The approaches that classified as corpus-based group are statistical approach and machine learning approach, and the remaining approaches are in dictionary-based group.

Several existing works of OM, e.g., Mcdonald, *et al*. (2007), Yessenalina, Yue and Cardie (2010), etc. revealed the trend of OM research in last few years. They are focusing on analysis in subtle level, mixed of different level of analysis and combine several approach of analysis. They give more fine grains of results and can also summarize as overall of satisfactions on products or services.

Definition in Opinion Mining

In commercial field, there are some important basic terminology and definition that related with "Opinions Mining" are described by Liu (2011: pp. 418-422) as follows:

Definition (object): An object ***O*** is an entity which can be a product, person, event, organization, or topic. It is associated with a pair, ***O***: ***(T, A)***, where ***T*** is a hierarchy of components (or parts), sub-components, and so on, and ***A*** is a set of attributes of ***O***. Each component has its own set of sub-components and attributes.

Example 1: A particular brand of cellular phone is an object. It has a set of components, e.g., *battery*, and *screen*, and also a set of attributes, e.g., *voice quality*, *size*, and *weight*. The battery component also has its set of attributes, e.g., *battery life*, and *battery size*.

Definition (opinion passage on a feature): An *opinion passage* on a feature *f* of an object *O* evaluated in *d* is a group of consecutive sentences in *d* that expresses a positive or negative opinion on *f*.

Definition (explicit and implicit feature): If a feature *f* or any of its synonyms appears in a sentence *s*, *f* is called an *explicit feature* in *s*. If neither *f* nor any of its synonyms appear in *s* but *f* is implied, then *f* is called an *implicit feature* in *s*.

Example 2: "*battery life*" in the following sentence is an *explicit feature*: "The *battery life* of this phone is too short". While, "This phone is too *large*". "*large*" is an *implicit feature* that imply to the Size feature.

Definition (opinion holder): The *holder* of an opinion is the person or organization that expresses the opinion.

Definition (opinion): An *opinion* on a feature *f* is a positive or negative view, attitude, emotion or appraisal on *f* from an opinion holder.

Definition (opinion orientation): The *orientation* of an opinion on a feature *f* indicates whether the opinion is *positive, negative* or *neutral*.

2.4.2 Machine Learning and Statistical approaches for Opinion Mining

As described in previous section (Overview of opinion mining), the opinion mining process consists of three sub-tasks: 1) Determining subjectivity

2) Determining polarity and 3) Determining strength of polarity. Determining subjectivity task aims to decide the given sentence comprise of factual or opinion. While the last two sub-tasks attempt to indicate the polarity direction of given opinion sentence and identify the strength of these polarity direction. Follow of these sub-tasks, the supervised machine learning is the most widely used technique that implemented in opinion mining process. This section explains some well-known features in opinion mining, supervised machine learning and statistical technique that implement in opinion mining tasks (Sukhum, Nitsuwat and Haruechaiyasak, 2011; Shelke, Deshpande and Thakre, 2012; Hajmohammadi, Ibrahim and Othman, 2012).

1) Feature types

To implement supervised machine learning technique in opinion mining, the appropriate feature set is a necessary component to train a machine learning model. There are several types of feature that used to train machine learning model as follows:

- Words: word is common type of feature that used in opinion mining process. It is basic structure of sentence. A word consists of sequence of consonants and vowels. In English, each word is separated with the blank space character. The punctuation character is used to indicate the boundary of sentence. While Asian language e.g. Chinese, Japanese, Thai, etc. does not have the punctuation marks to identify word or sentence boundary.

- Part-Of-Speech (POS): derived from word feature, POS is used to indicate the function of each word in sentence. There are several types of POS defined depend on their language. In WordNet, four types of POS include Noun, Verb, Adjective and Adverb are defined. In ORCHID and NAiST corpus (as mentioned in Section 2.2.1), several type of POS with more subtle categories are defined.

- Cues words: these words are the context word in sentence. These words are useful to imply the given sentence consists of important information such as "อยากให้" (wish), "ควรจะ" (shall), etc. Also, includes "ด้วยเหมือนกัน" (too), "แต่ว่า" (but), and the negation word.

- Keywords and synonyms: Keyword and synonym words are phrases or sets of word feature. Keywords are the important words in the interested domain. Synonyms are the different words that have the same meaning with a word.

- Term position: the position is a feature type which probably effects on decision of the polarity of sentence. This is the numeral value that obtained from position of words or keywords in a sentence or paragraph. For example, In English sentence, many words in text paragraph contains positive words throughout; however, there is a presence of a negative sentiment at the end of sentence. It will influence on deciding role to determine the sentiment of sentence.

2) Feature representation

To analyze those aforementioned features, there are two types of feature representation includes 1) Term Frequency-Inverse Document Frequency and 2) N-gram (Pang, Lee and Vaithyanathan, 2002; Jotheeswaran, Loganathan and Madhu Sudhanan, 2012).

- Term Frequency-Inverse Document Frequency (TF-IDF): TF-IDF is a common type of data representation. This model is a vector space model that considers the text paragraph as documents. A document (*d*) is represented as vector (*v*) in the dimensional space of documents (*D*). The Term-Frequency (*TF*) is the number of occurrence of this term is given by term frequency which denoted by *freq(x,d)*. The association of a term *x* with respect to the given document *d* is measured by the term-frequency matrix *TF(x,d)*. The term frequencies are assigned values depending on the occurrence of the terms. *TF(x,d)* is assigned either zero, if the document does not contain the term *x*. Otherwise, The number could be set as *TF(x,d)* = 1 when term *x* occur in the document *d*. Beside direct use of term frequency, the relative term frequency is a kind of term occurrence representation. It is the term frequency versus the total number of occurrence of all terms in document. The term frequency is generally normalized by Equation 2.14:

$$TF(x,d) = \begin{cases} 0 & freq(x,d) = 0 \\ 1+\log\left(1+\log\left(freq(x,d)\right)\right) & Otherwise \end{cases} \tag{2.14}$$

The Inverse Document Frequency (*IDF*) represents the scaling factor of *TF*. The importance of a term *x* is scaled down if term occurs frequently in many documents due to its reduced discriminative power. *IDF(x)* is defined as follows in Equation 2.15:

$$IDF(x) = \log\left(\frac{1+|D|}{|d_x|}\right) \tag{2.15}$$

Where $|D|$ is total number of document in corpus, $|d_x|$ is the number of documents that contains term *x*. According to Equation 2.14-2.15 the complete of *TF-IDF* model is obtained by multiplication of each *TF(x,a)* with their own *IDF(x)* value. In case of misspelling, error typing, stemming, the syntactic or semantic similarity computation can apply to decide the word is occurred in a document.

Moreover, the dimensionality reduction technique such as Principal Component Analysis, Chi-Square Attribute selection, Information-Gain, etc. can used to obtain the importance features.

- N-grams: Instead of using individual words as features. A technique called "*n*-gram" is invented to generate dataset. The *n*-gram dataset is generated by placing a small window over a sentence or a text, in which only *n* words are visible at the same time. The simplest *n*-gram dataset is Unigram model (*n*=1). This is a model in which we only look at one word at a time. In fact, *n*-grams start to become interesting when *n* is two (a bigram) or greater. For example, a sentence "อาจารย์พูดเร็วไปนิดนึง" (Teacher speaks a little faster). After text segmentation process, the sequences of term "อาจารย์/ พูด/ เร็ว/ ไป/ นิดนึง" are obtained. Variant length of *n*-gram data can generate from this term sequences, For example:

Unigram: "อาจารย์" , "พูด", "เร็ว", "ไป", "นิดนึง"

Bigram: "อาจารย์_พูด", "พูด_เร็ว", "เร็ว_ไป", "ไป_นิดนึง"

Trigram: "อาจารย์_พูด_เร็ว", "พูด_เร็ว_ไป", "เร็ว_ไป_นิดนึง"

N-gram could apply with TF-IDF model or directly uses as features in machine learning technique. In same fashion, *n*-gram can use with the Part-Of-Speech features.

3) Machine learning and Statistical approaches

The machine learning provided benefits to decrease time-consuming of human activity and still retain the efficiency equivalent with the human performance. Recently, the machine learning becomes the popular technique that uses in several tasks of opinion mining e.g. Wiebe and Riloff (2005) used the Naïve Bayes classifier to identify subjective sentence, Bullington, Endres and Rahman (2007) classified the genre of answer in open-ended question with Support Vector Machine. Hu and Liu (2006) extracted product feature with the Class Sequential Rule (an extended of association rules), Pang, Lee and Vaithyanathan (2002) classifies the given sentence into binary-categories (positive or negative), etc. This section explains the four well-known supervised machine learning technique that used in opinion mining tasks including: 1) *k*-Nearest Neighbors, 2) Association Rules, 3) Naïve Bayes, 4) Support Vector Machine, and 5) Artificial Neural Network.

3.1) k-Nearest Neighbors

"k-Nearest Neighbors" (kNN) is a lazy learning method in the sense that no model is learned from the training data. Learning only occurs when a text example needs to be classified. *k*NN is simple and most yet effective classes of classification algorithms in use. Their principle is based on the assumption that, the class of a new yet unseen occurrence is likely to be that of the majority of its closest "neighbor" instances from the training set. Thus the *k*-nearest neighbor algorithm works by inspecting the *k* closest instances in the data set to a new occurrence that needs to be classified, and making a prediction based on what classes the majority of the *k* neighbors belong to. The notion of closeness is formally given by a distance function between two points in the attribute space. An example of distance function typically used is the standard Euclidean distance between two points in an *n*-dimensional space, where *n* is the number of attributes in the data set. The *k*NN algorithm is shown in Algorithm 2.1.

Algorithm 2.1: Basic *k*NN Algorithm

Input : *D*, the set of training objects,

z, the test object which is a vector of attribute values, and

L, the set of classes label

Output : $c_z \in L$, the class of ***z***

Steps :

For Each object **y** $\in D$ **do**

Compute *d*(**z**,**y**), the distance between **z** and **y**;

end

Select $N \subseteq D$, the set (neighborhood) of *k* closest training object for ***z***;

$$c_z = \arg\max_{v \in L} \sum\nolimits_{y \in N} I(v = class(c_y))$$

Where $I(\bullet)$ is an indicator function that returns the value 1 if its argument is true and 0, otherwise.

Liu (2011) explain using of *k*NN algorithm in sentiment classification as follows: Suppose we have two classes of data that is Positive class (♦) and Negative class (☐). The test data point is (⦿). If 1-nearest neighbor (*k*=1) is used, the test point will be classified as Positive class. If 2-nearest neighbor (*k*=2) is used, the class cannot be decided. Because of there are different classes of two closest neighborhoods. If 3-nearest neighbor (*k*=3) is used, the Positive class is assigned corresponding with the majority class of its closest neighborhoods (as depicted in Figure 2.6).

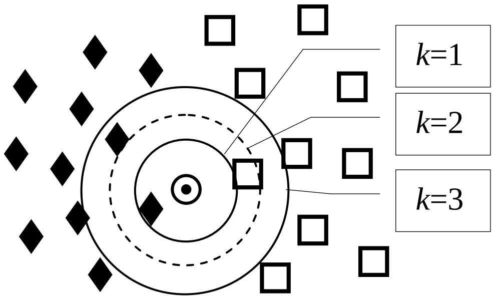


Figure 2.6 An example of *k*NN classification

3.2) Association Rules

"Association Rules" (AR) is a mining technique that attempts to extract pattern of data co-occurrence relationships and represents in set rules (Antecedent and Consequent) with their satisfaction score (Support and Confidence). The classic application of association rule mining is used with the market basket data, which aims to discover how items purchased by customers in a store are associated. An example association rule is

"Cheese", "Beef" $\rightarrow$ "Beer" [*Support=10%, Confidence=80%*]

A rule consist of two measurements of rule strength that are Support and Confidence. This rule says that there are 10% of customers buy "Cheese", "Beef" and "Beer" together, and those who buy "Cheese" and "Beef" also buy "Beer" with 80% of the time.

The formal statement of association rule can explain as follows (Agrawal, Imielinski and Swami, 1993): Let $I = \{i_1, i_2, \ldots, i_m\}$ be a set of items. Let D be a set of transactions, where each transaction T is a set of items such that $T \subseteq I$. Associate with each transaction is a unique identifier, called its *TID*. We say that a transaction T contains X, a set of some items is I, if $X \subseteq T$. An association rule is an implication of the form $X \rightarrow Y$, where $X \subset I$, $Y \subset I$, and $X \cap Y = \emptyset$. The rule $X \rightarrow Y$ holds in the transaction set D with *confidence* c, if $c\%$ of transactions in D that contain X also contain Y. The rule $X \rightarrow Y$ has *support* s in the transaction set D, if $s\%$ of transactions in D contains $X \cup Y$. The best known mining association rule algorithm is the Apriori algorithm as shown in Algorithm 2.2.

Algorithm 2.2: Apriori algorithm (Liu, 2011)

Input : T, the set of transaction,
    minsup, the threshold of minimum support,
Output : F, the set of overall frequent itemsets
Steps :
  $C_1 \leftarrow$ all transaction T;
  $F_1 \leftarrow \{f \mid f \in C_1, f.count/n >= minsup\}$ # find 1-frequency itemsets
  For (k=2; $F_{k-1} \neq \emptyset$; k++) **do**   # find k-frequency itemsets
    $C_1 \leftarrow Candidate\text{-}gen(F_{k-1})$;   # call Algorithm 2.2.1
    For Each $t \in T$ **do**
      For Each $c \in C_k$ **do**
        If c is contained in t **then** $c.count$++;
      end
    end
    $F_k \leftarrow \{ c \in C_k \mid c.count/n >= minsup\}$
  end
  return $F \leftarrow \{F_1 \cup \ldots \cup F_{k-1} \cup F_k\}$;

Algorithm 2.2.1: Candidate-gen function (used in Algorithm 2.2)

Input : F_{k-1} , the set of transaction that have support value >= *minsup*,

Output : C_k , the candidate of frequent itemsets

Steps :

$C_k \leftarrow \varnothing$;

Forall $f_1, f_2 \in F_{k-1}$

with $f_1 = \{i_1, \ldots, i_{k-2}, i_{k-1}\}$ and $f_2 = \{i_1, \ldots, i_{k-2}, i'_{k-1}\}$

and $i_{k-1} < i'_{k-1}$ **do**

$c \leftarrow \{i_1, \ldots, i_{k-1}, i'_{k-1}\}$; // join the two itemsets f_1 and f_2

$C_k \leftarrow C_k \cup \{c\}$;

For Each (k-1)-subset s of c **do**

If ($s \notin F_{k-1}$) **then** delete c from C_k ;

End

End

Return C_k ;

Association rule mining is loop works in two steps:

1) Generate all frequent itemsets: A frequent itemset is an itemset that has transaction Support above *minsup*.

2) Generate all confident association rules from the frequent itemsets: A confident association rule is a rule with Confidence above *minconf*.

In classification tasks, a technique called “Classification Based on Association (CBA)” is a widely used technique in several fields (Liu, Hsu and Ma, 1998; Kim *et al.*, 2009). In opinion mining, a type of rules set that obtain by an extended of association rule called “Class Association Rule (CAR)” is used with this technique. The idea to generate rules of CAR is a bit different from Apriori algorithm, in aspect of all selected rules are fixed as consequent values as Class label.

To classification with CBA, there are three rules should be concerned to decide the class for the new unknown data point when several association rules are appeared (Waiyamai and Pongsiripreeda, 2005):

1) If the confidence value of rule no. 1 is greater than the rule no.2, then rule no.1 is important than rule no.2.

2) If the confidence value of rule no. 1 is equals to rule no.2, then considered the support value. If the support value of rule no. 1 is greater than rule no.2, then rule no.1 is important than rule no.2.

3) If both of confidences and supports of all rules are equal, the rule that early generating is important than another rules.

However, if several rules have same confidence and support values are existed. The majority classes that obtained for these rules are assigned to the new unknown data.

3.3) Naïve Bayes

"Naïve Bayes" (NB) is a simple probabilistic model based on the Bayes rule along with a strong independence assumption. It involves a simplifying conditional independence assumption. In text classification tasks, Naïve Bayes is an effective algorithm; because of the conditionally independent of the data on each other. This assumption does not affect the accuracy in text classification by much, but this assumption makes fast classification algorithms applicable for the problem. Moreover, it is particularly suited when the data inputs are high-dimensionality. Naïve Bayes classifier assigns the class $c^* = \text{argmax}_c\, P(c \mid x)$, to a given document x. This classifier is based on Bayes' rule as shown in Equation 2.16.

$$P(c\,|\,x) = \frac{P(c)P(x\,|\,c)}{P(x)} \tag{2.16}$$

Where $P(x)$ plays no role in select c^*. To estimate the term $P(x\,|\,c)$, Naïve Bayes decomposes it by assuming the x_i are conditionally independent given c class as shown in Equation 2.17.

$$P_{NB}(c\,|\,x) := \frac{P(c)\left(\prod_{i=1}^{m} P(x_i\,|\,c)\right)}{P(x)} \tag{2.17}$$

Where m is the number of features and x_i is the feature vector.

Consider a training method consists of a relative frequency estimation $P(c)$ and $P(x_i\,|\,c)$. Despite its simplicity and the fact that it's conditional independence assumption clearly does not hold in real-world situations. Naïve Bayes tends to perform well and optimal for certain problem classes with highly dependent features. The computational example of Naïve Bayes classifier can be illustrated below (Kantaradzic, 2003):

1) Given training dataset consisting of three features (*A1*, *A2* and *A3*) with target class (*C*). The objective is to assign the class to the new unknown data point, X = {*A1=1*, *A2=2*, *A3=2*, *C*=?}. The detail of training dataset is as follows:

A1	***A2***	***A3***	***C***
1	2	1	1
0	0	1	1
2	1	2	2
1	2	1	2
0	1	2	1
2	2	2	2
1	0	1	1
1	***2***	***2***	***?***

2) Compute prior probabilities $P(C)$ of the classes:

$P(C=1) = 4/7 = 0.5714$ and $P(C=2) = 3/7 = 0.4286$

3) Compute conditional probabilities $P(x_t \mid c_i)$ for every features value of the new unknown $X = \{A1=1, A2=2, A3=2, C=?\}$:

$P(A1 = 1 \mid C=1) = 2/4 = 0.50$ and $P(A1 = 1 \mid C=2) = 1/3 = 0.33$

$P(A2 = 2 \mid C=1) = 1/4 = 0.25$ and $P(A2 = 2 \mid C=2) = 2/3 = 0.66$

$P(A3 = 2 \mid C=1) = 1/4 = 0.25$ and $P(A3 = 2 \mid C=2) = 2/3 = 0.66$

4) Under the assumption of conditional independence of features, compute conditional probabilities $P(X \mid C)$ will be:

$$
\begin{aligned}
P(X \mid C=1) &= P(A1 = 1 \mid C=1) \times P(A2 = 2 \mid C=1) \\
&\quad \times P(A3 = 2 \mid C=1) \\
&= 0.50 \times 0.25 \times 0.25 = 0.03125 \\
P(X \mid C=2) &= P(A1 = 1 \mid C=2) \times P(A2 = 2 \mid C=2) \\
&\quad \times P(A3 = 2 \mid C=2) \\
&= 0.33 \times 0.66 \times 0.66 = 0.14375
\end{aligned}
$$

5) Obtain the proportional value of $P(C|X)$ by multiplying these conditional probabilities $P(X|C)$ with corresponding prior probabilities $P(C)$:

$$
\begin{aligned}
P(C=1 \mid X) &\approx P(X \mid C=1) \times P(C=1) \\
&= 0.03125 \times 0.5714 = 0.0179 \\
P(C=2 \mid X) &\approx P(X \mid C=2) \times P(C=2) \\
&= 0.14375 \times 0.4286 = 0.0616
\end{aligned}
$$

6) Find their maximum of probabilities value:

$$P(C=?\mid X) = argmax\{P(C=1\mid X), P(C=2\mid X)\}$$

$$= argmax\{0.0179, 0.0616\} = 0.0616$$

According to $\text{argmax}_c\ P(c \mid x)$ results, the new unknown data $X = \{A1=1, A2=2, A3=2\}$ is belongs to the class $C = 2$ with the maximum probability value 0.0616.

3.4) Support Vector Machine

"Support Vector Machine" (SVM) is a supervised machine learning technique which developed by Vapnik in 1995. It has been applied successfully in many text classification tasks and provides several principal advantages: first, SVM is robust in high dimensional spaces; second, any feature is relevant to use in classification; finally, it is robust when there is a sparsely set of samples (Saleh, MartíN-Valdivia, Montejo-RáEz and UreñA-LóPez, 2011). In opinion mining, Support Vector Machines have been applied in order to classify a set of opinions as positives or negatives.

The basic idea of SVM is to find an optimal hyperplane to separate two classes with the largest margin from pre-classified data. After this hyperplane is determined, it is used for classifying data into two classes based on which side they are located. By applying appropriate transformations (kernel function) to the data spaces, then compute the separating hyperplane. SVM classification can be depicted as Figure 2.7.

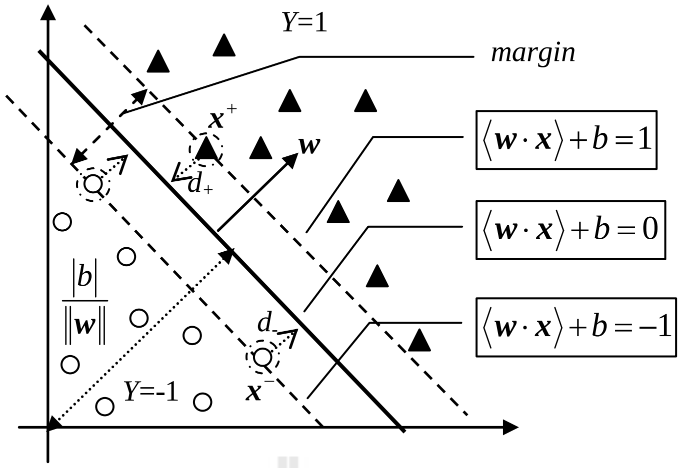


Figure 2.7 Supporting hyperplanes and margin of SVM

To build a classifier, SVM finds a linear function as Equation 2.18.

$$f(x) = \langle \boldsymbol{w} \cdot \boldsymbol{x} \rangle + b. \tag{2.18}$$

So that an input vector x_i is assigned to the positive class if $f(x_i) \geq 0$, and to the negative class otherwise, as Equation 2.19.

$$y_i = \begin{cases} 1 & if \ \langle w \cdot x \rangle + b >= 0 \\ -1 & if \ \langle w \cdot x \rangle + b < 0 \end{cases} \tag{2.19}$$

With the margin of SVM is $(d_+ + d_-) = \frac{2}{\|\boldsymbol{w}\|}$

Khairnar and Kinikar (2013) demonstrated a computational example of linear SVM classifier with 1-dimensional of dataset as follows:

1) Given training dataset consisting of one feature (*X1*) with target class (*C*).

X1	*C*
0	+1
1	-1
2	-1
3	+1

2) Kernel function plays vital role in SVM classification. The appropriate transformation function (kernel function) uses to map these data points to feature space. Commonly used kernel functions are "Linear function", "Polynomial function" and "Gaussian Radial Basis Function (RBF)" (Liu, 2011).

To demonstrate, a simple polynomial function is selected, $K(\boldsymbol{x}) = \langle \boldsymbol{x} \rangle^{d}$, where d = 2, is used. This means multiplying the *X1* feature value to power of 2 ($X1^2$). This mapping result is stored in *X2* feature.

X1	*X2 = K(X1)*	*C*
0	*0*	+1
1	*1*	-1
2	*4*	-1
3	*9*	+1

3) Finding the three hyperplanes that correspond with following functions;

$\langle \boldsymbol{w} \cdot \boldsymbol{x} \rangle + b = 1$ (Positive class),

$\langle \boldsymbol{w} \cdot \boldsymbol{x} \rangle + b = -1$ (Negative class), and

$\langle \boldsymbol{w} \cdot \boldsymbol{x} \rangle + b = 0$ (Hyperplane).

These Equations can expand as follows:

- Positive class: $w_1x_1 + w_2x_2 + b = 1$

- Negative class: $w_1x_1 + w_2x_2 + b = -1$

- Hyperplane: $w_1x_1 + w_2x_2 + b = 0$

4) Solve w and b for Positive and Negative classes.

- Positive class: $w_1x_1 + w_2x_2 +b = 1$

$w_1(0) + w_2(0) + b = 1$ (data points no.1) and

$w_1(3) + w_2(9) + b = 1$ (data points no.4)

- Negative class: $w_1x_1 + w_2x_2 + b = -1$ (data points no.2 and no.3)

$w_1(1) + w_2(1) + b = -1$ (data points no.2) and

$w_1(2) + w_2(4) + b = -1$ (data points no.3)

Using linear algebra with this simple example, the optimal solution of above systematic Equations are $w_1 = -3$, $w_2 = 1$, and $b = 1$. Generally, numerous of features in training dataset, the parameter estimation of SVM is complicated process. Transforming of these Equation into Lagrangian form and using a numerical optimization process called "Quadratic programming" is find solution.

5) Substitution these optimal value: $w_1 = -3$, $w_2 = 1$, and $b = 1$ in systematic Equations. The hyperplane of each classes are obtained as follows:

- Positive class: $w_1x_1 + w_2x_2 + b = 1$

$(-3)x_1 + (1)x_2 + 1 = 1$

$x_2 = 3x_1$

- Negative class: $w_1x_1 + w_2x_2 + b = -1$

$(-3)x_1 + (1)x_2 + 1 = -1$

$x_2 = -2 + 3x_1$

- Hyperplane class: $w_1x_1 + w_2x_2 + b = 0$

$(-3)x_1 + (1)x_2 + 1 = 0$

$x_2 = -1 + 3x_1$

6) New co-ordinate (*X2*) of each hyperplane is produced as follows:

X1	***X2***	***Hyperplane (X2)***	***Positive (X2)***	***Negative(X2)***	***C***
0	*0*	-1	*0*	-2	+1
1	*1*	2	3	*1*	-1
2	*4*	5	6	*4*	-1
3	*9*	8	*9*	7	+1

The margin of SVM can computed by $\frac{2}{\|\mathbf{w}\|}$:

$$\text{Margin} = \frac{2}{\sqrt{w_1^2 + w_2^2 + \ldots + w_i^2}} = \frac{2}{\sqrt{(-3)^2 + (1)^2}} = 0.6324555$$

To classify, the new unknown data point *X1*=2.8, $w_1 = -3$, $w_2 = 1$, and $b = 1$. Substitute *X1* value and compute *X2* with polynomial kernel function.

$$\langle w \cdot x \rangle + b = w_1x_1 + w_2x_2 + b$$

$$= -3(2.8) + 1(2.8^2) + 1 = 0.44$$

According to Equation 2.18, this new unknown data point obtained result greater than 0, it belongs to the +1 class.

Beside, using SVM in classification task, there is development of SVM for function estimation called “Sequential Minimal Optimization algorithm for Support Vector Machine Regression (SVR)” (Smola and Scholkopf, 2003). SVR has the same properties as the traditional SVM which using the margin maximization and kernel trick for non-linear mapping. The goal of SVR function is to estimate the parameters weight vector (***w***) and bias (***b***) of function that best fit to the training data. By approximating all pairs (x_i,y_i) from training dataset, while maintain the differences between estimated values (***y′***) and real values (***y***) under the soft margin (ε precision). This idea can be depicted as Figure 2.8.

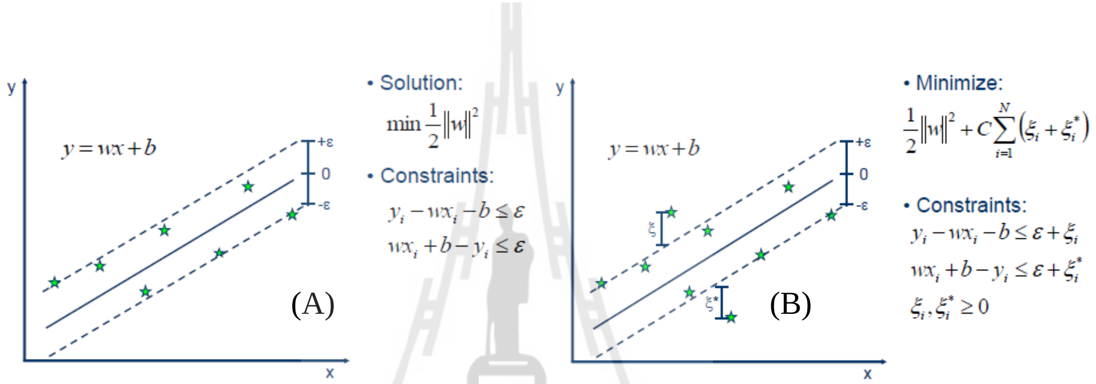


Figure 2.8 (A) Traditional SVM and (B) SVM Regression

(Smola and Scholkopf, 2003)

Similarly traditional SVM, the SVR can write as a convex optimization problem. However, traditional SVM is not allowing some error that data point are exceeds the ε margin. To deal with noise data in the training data, some additional variables are applied in the soft margin of SVR function. The slack variables (ξ) deal with infeasible constraints of the optimization problem by imposing the penalty to the excess deviations which larger than ε, and an arbitrary constant C ($C > 0$) is the trade-off parameter between the margin size and amount of errors. The SVR can be revised as a primal optimization problem as Equation 2.20.

$$\text{Minimize} \quad L(\boldsymbol{w},\boldsymbol{\xi}) = \frac{1}{2}\|\boldsymbol{w}\|^2 + C\sum_i (\xi_i^2, \hat{\xi}_i^2), C > 0$$

$$\text{Subject to} \quad \begin{cases} y_i - \langle \boldsymbol{w}, \boldsymbol{x}_i \rangle - b \le \varepsilon + \xi_i \\ \langle \boldsymbol{w}, \boldsymbol{x}_i \rangle + b - y_i \le \varepsilon + \hat{\xi}_i \\ \quad \xi_i, \hat{\xi}_i \ge 0 \end{cases} \tag{2.20}$$

To obtained the optimize solution of weight vector (***w***), slack variable (ξ) and bias variable (*b*), Equation 2.20 would be solved by using the quadratics programming method, in Lagrangian dual problem form (See more details, Smola and Scholkopf, 2003).

3.5) Artificial Neural Network

"Artificial Neural Network" (ANN) is a machine learning technique which several previous studies indicated that it provided good performance for many classification task (Sharma and Dey, 2012; Ghiassi, Skinner and Zimbra, 2013; Khatri, Singhal and Johri, 2014). The inspiration of ANN is biological neural network model. The basic computational unit of ANN is a neuron. A neuron consists of several dendrites which used to retrieve inputs data. These inputs were computed and aggregated inside a cell body, than a result was passed to the terminal axon which connects with other dendrites (synapse) of next neuron node. Based on this biological characteristics, ANN simulate a set of computational processors which interconnected and operated in parallel fashion in each own small sphere (as depict as Figure 2.9).

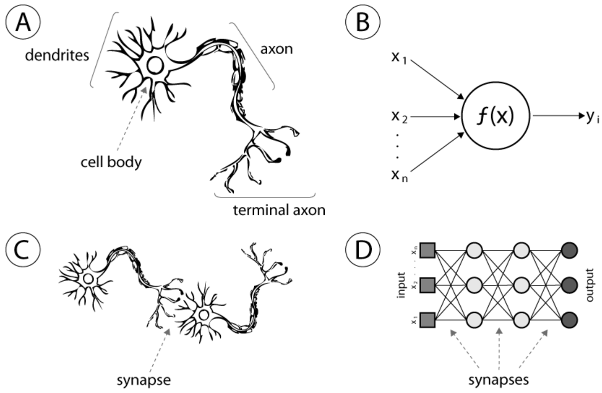


Figure 2.9 Biological and Artificial Neural Network Model

(Maltarollo, Honório and Ferreira da Silva, 2013)

In mathematical terms, a neuron of ANN (*k*) is the weight sum of multiplication between inputs (*x*) and their weight (*w*) in *m*-dimensional. This process can express in vector notation as a scalar product of two *m*-dimensional vectors (as shown in Equation 2.21).

$$net_k = X \cdot W \tag{2.21}$$

Where

$$X = \{x_0, x_1, x_2, ..., x_m\}, \quad W = \{w_{k0}, w_{k1}, w_{k2}, ..., w_{km}\}$$

Finally, an artificial neuron computed the output (y_k) with a certain function which used net_k value as input. This function called "Activation functions" (Equation 2.22).

$$y_k = f(net_k) \tag{2.22}$$

Some commonly used activation function are given in Table 2.6

Table 2.6 A neuron's common activation function (Kantaradzic, 2003, p. 198)

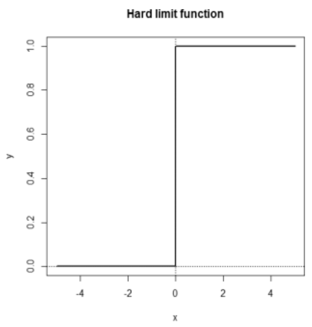
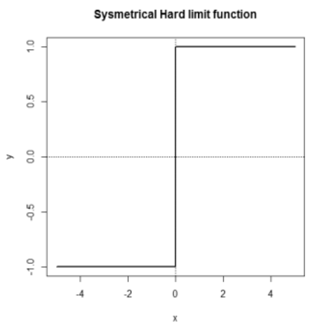
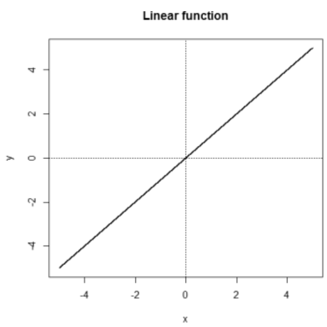
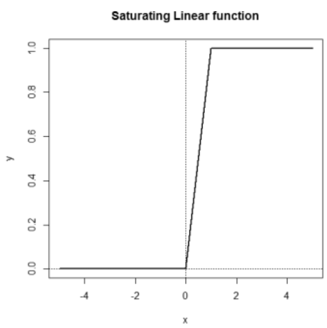
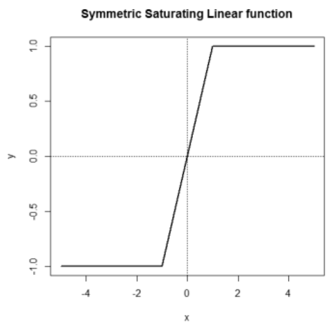
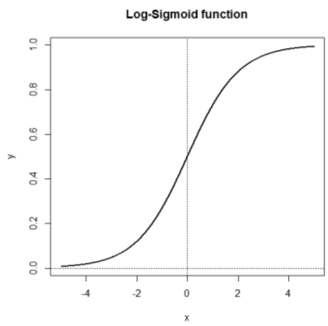
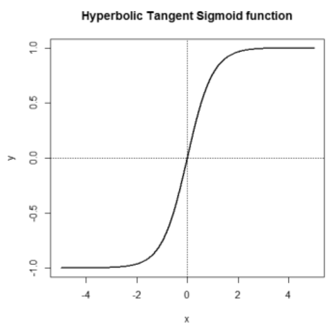
Activation Function	Input / Output Relation	Example graphs
Hard Limit	$y=\begin{cases}1 & if\ net \geq 0\\ 0 & if\ net < 0\end{cases}$	
Symmetrical Hard Limit	$y=\begin{cases}1 & if\ net \geq 0\\ -1 & if\ net < 0\end{cases}$	
Linear	$y = net$	
Saturating Linear	$y=\begin{cases}1 & if\ net > 1\\ net & if\ net \geq 0 \,\&\, net \leq 1\\ 0 & if\ net < 0\end{cases}$	

Table 2.6 A neuron's common activation function (continued)

Activation Function	Input / Output Relation	Example graphs
Symmetric Saturating Linear	$y = \begin{cases} 1 & if\ net > 1 \\ net & if\ net \geq -1 \,\&\, net \leq 1 \\ -1 & if\ net < -1 \end{cases}$	
Log-Sigmoid	$y = \dfrac{1}{1+e^{-net}}$	
Hyperbolic Tangent Sigmoid	$y = \dfrac{e^{net} - e^{-net}}{e^{net} + e^{-net}}$	

There are several kind of Artificial Neural Network Models were developed e.g. Discrete Hopfield, Kohonen Self-Organizing Map, Fuzzy Associative Memory, Boltzmann Machine, Perceptron, Backprogagation, etc. (Suh, 2012). In learning process of these ANN model, there are four common parameters which are affected and used to determine performance of model as follows:

1) Number of Hidden Layers: in most neural network models, the number of hidden layers is either manually decided at the beginning or is determined automatically by the training dataset. For example, a multiple-layer perceptron with continuous output, used non-linear function as activation function, there is one hidden layer with an arbitrarily larger number of neuron nodes. However, there is no unified theory yet as to how many hidden layers or nodes are needed.

2) Number of Hidden Nodes: there is no way of determining good network architecture just from the number of inputs and outputs. Therefore, simply trying several networks with different number of hidden nodes, and choose the one with the least estimated generalization error is the best technique.

3) Early Stopping: Sometime neural-network model was learned very long time, because it involves training and validation. To reduce this learning time, a method called "early stopping" is used. It can perform as follows:

- Divide the available data into training and validation sets. This can decrease the complexity of data.
- Use a large number of hidden nodes. The greater number of nodes make easier to distinguish and generated the useful rules. But this also increases calculation time.
- Use very small random initial values. An initial value usually setting between -0.1 to 0.1. This small value prevents all nodes reach the same state.
- Use a slow learning rate. Slow learning helps to avoid oscillation of the result.
- Compute the validation error rate periodically during training.
- Stop training when the validation error rate "starts to go up".

4) Convergence Curve: To determine how many iterations process should be stopped? The total mean-square error for the neural-network can be used to determine the oscillation rate for convergence.

For classification, an Artificial Neural Network need to learning pattern from training data, with some parameter setting as mentioned above. An example learning process of ANN (Backpropagation) is illustrated in Algorithm 2.3.

Algorithm 2.3: Backpropagation Learning process (Suh, 2012)

1. Set the parameter of the network.
2. Set the uniform random numbers for weight vector W_{xh}, W_{hy} and bias vector θ_h , θ_y.
3. Obtain an input training vector X and the desired output vector T.
4. Calculate the output vector Y as follows:

$$net[h] = \sum_i W[i][h] \times X[i] - \theta[h]$$

4.1 Calculate the output vector H in the hidden layer.

4.2 Calculate the output vector Y (used activation function).

$$net[j] = \sum_i W[h][j] \times H[h] - \theta[j]$$

$$Y[j] = f(net[j])$$

5. Calculate the value δ.

$$\delta_j = Y_j(1 - Y_j)(T_j - Y_j)$$

5.1 Calculate the value δ_j in the output layer.

5.2 Calculate the value δ_h.

$$\delta_h = H_h(1 - H_h)\sum_j W_{hj}\delta_j$$

6. Adjust the weight.
   6.1 At the output layer: $\Delta W_{y_{hi}} = \eta\delta_j H_k$, $\Delta\theta_{y_j} = -\eta\delta_j$
   6.2 At the hidden layer: $\Delta W_{x_{ih}} = \eta\delta_h X_i$, $\Delta\theta_{h_h} = -\eta\delta_h$
7. Update W and θ.
   7.1 At the output layer:
   $W_{y_{hj}} = W_{y_{hj}} + \Delta W_{y_{hj}}$, $\theta_{y_j} = \theta_{y_j} + \Delta\theta_{y_j}$
   7.2 At the hidden layer:
   $W_{h_{ih}} = W_{x_{ih}} + \Delta W_{x_{hj}}$, $\theta_{h_h} = \theta_{h_h} + \Delta\theta_{h_h}$
8. Repeat steps 3-7 until the network converges.

With the advantage characteristic of ANN that deal with non-linearity problem. Besides, using ANN in classification task, a type of ANN for regression task was proposed by Hall *et. al.*, (2009) called "MLPregressor". This ANN is implemented in "WEKA" application. It consists of a single-hidden layer of Multi-Layer Perceptron (MLP). The difference of this model is using numerical optimization method called "Broyden-Fletcher-Goldfarb-Shanno (BFGS) method" to obtain optimized weight vector. These optimized weights are given by minimizing based on the squared error plus a quadratic penalty (ridge parameter). The ridge parameter is used to determine the penalty on the size of the weights. The "quadratic penalty" refers to the squared sum of weights exclude the non-bias, which is multiplied by the ridge parameter before being added to half the mean-squared error. All attributes and target output are standardized. Instead of linear function, this regression model used the logistic function as the activation function in each units of model.

3.6) Linear Regression

"Linear Regression" is a statistical technique to estimate or predict an output value from given input data. The mechanic of regression is finding the best line to fit between variables, so that one variable can be used to predict the other. It can formal written as Equation 2.23 (Bhardwaj, n.d.; Kantaradzic, 2003).

$$Y = \alpha + \beta X \tag{2.23}$$

Where Y is dependent variable vector (responses), X is independent variable vector (predictor), and $\alpha,\ \beta$ are regression coefficient. These coefficients can be solved by the method of least squares, which minimizes the error between the actual data points and the estimated line. The residual sum of squares is often called the sum of squares of the error about the regression line and it is denoted by SSE (as shown in Equation 2.24).

$$SSE = \sum_{i=1}^{n} e_i^2 = \sum_{i=1}^{n} (y_i - y_i')^2 = \sum_{i=1}^{n} (y_i - \alpha - \beta x_i)^2 \tag{2.24}$$

Where y is the real output value given in the data set, and y' is a responses value obtained from the model. Differentiating SSE with respect to α and β can written as Equation 2.25-2.26.

$$\frac{\partial SSE}{\partial \alpha} = -2\sum_{i=1}^{n} x_i (y_i - \alpha x_i - \beta) \tag{2.25}$$

$$\frac{\partial SSE}{\partial \beta} = -2\sum_{i=1}^{n} (y_i - a x_i - \beta) \tag{2.26}$$

Setting these partial derivatives equal to zero (minimization of the total error) and solve for the α and β, then re-arrange these result. The coefficient α and β are obtained as Equation 2.27-2.28.

$$\alpha = \left(\frac{\sum_{i=1}^{n} y_i}{n} \right) - \beta \left(\frac{\sum_{i=1}^{n} x_i}{n} \right) \tag{2.27}$$

$$\beta = \frac{\sum_{i=1}^{n} y_i x_i - \frac{\sum_{i=1}^{n} y_i \sum_{i=1}^{n} x_i}{n}}{\sum_{i=1}^{n} x_i^2 - \frac{\left(\sum_{i=1}^{n} x_i\right)^2}{n}} \tag{2.28}$$

For example, given the sample data in the form of a table (Figure 2.10 (left)). Computing the α and β coefficient follow the Equation 2.27 and 2.28. The regression line can depict as Figure 2.10 (right).

x	*y*
1	3
8	9
11	11
4	5
3	2

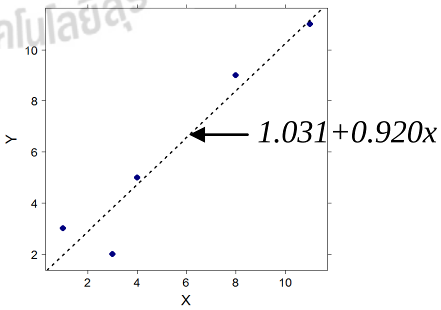


Figure 2.10 Linear regression line

Linear function is a simple case of prediction model with one input variable. For several input variables, linear function is extends to Multiple Linear

Regression model (MLR). MLR is used to model the linear relationship between a dependent variable and one or more independent variables. MLR is based on least squares: the model is fit such that the sum-of-squares of differences of observed and predicted values is minimized. The model expresses the value of a dependent variable as a linear function of one or more predictor variables and an error term (as Equation 2.9).

$$y_i = \alpha + \beta_1 x_{i,1} + \beta_2 x_{i,2} + \ldots + \beta_k x_{i,k} + e_i \tag{2.9}$$

Where $x_{i,k}$ is value of k^{th} input values, α is regression constant, β_i are coefficient on the k^{th} inputs and e is error term. With numerous of coefficient variables estimation, the numerical iteration technique such as Newton-Raphson method, Conjugate Gradient method, Expectation–Maximization method were popular used to obtain the optimal solution instead of using Linear algebra.

These statistical approaches and well-known machine learning technique are wildly used in several tasks of mining process. This work would experiment with these well-known machine learning techniques on Thai student's feedback. The performance of machine learning on several types of features are compared and presented in next chapter.

2.5 Related work

2.5.1 Opinion Mining in Non-Educational field

In the last decade, OM was an attractive field to study and review by many researchers e.g., Abbasi *et al.* (2008), Zhou and Chaovalit (2008), Tsytsarau and

Palpanas (2012) summarized OM research from 1997 to 2009. Continuing from the previous studies, this study review recent trend of OM research starting from 2010 to present and summarize in three perspectives as depicted in Figure 2.5. These three perspectives consist of: 1) *Research area*: the areas of OM that previous studies are concerned. 2) *Level of analysis*: these levels of OM that previous studies are analyzed, and 3) *Analysis approaches*: the analysis approach that previous studies are used. The selected of previous studies on OM with their experimental dataset are shown in Table 2.7.

Table 2.7 Selected previous studies on OM (Non-Educational field).

	Research areas			**Levels of analysis**				**Analysis approaches**				
Authors	**R1**	**R2**	**R3**	**L1**	**L2**	**L3**	**L4**	**A1**	**A2**	**A3**	**A4**	**Experimental Dataset**
Year 2011												
Bollegala, Weir and Carroll (2011)	•	•			•	•			•	•		Product review
Drury and Almeida (2011)		•			•	•	•		•		•	News corpus
Engonopoulos *et al*. (2011)		•			•	•			•	•		Product review
Hu and Li (2011)		•		•	•					•		Product review
Neviarouskaya, Prendinger and Ishizuka (2011)	•				•	•		•		•		Develop Holistic lexicon
Sarvabhotla, Pingali and Varma (2011)		•		•	•				•	•		Movie review
Wang and Liu (2011)			•		•					•		Telephone conversation
Wu and Tan (2011)		•		•					•			Product review
Xia, Zong and Li (2011)		•				•			•			Movie review
Zhang et al. (2011)		•				•	•	•		•		Product review

Table 2.7 Selected previous studies on OM (Non-Educational field) (continued)

Authors	Research areas			Levels of analysis				Analysis approaches				Experimental Dataset
	R1	R2	R3	L1	L2	L3	L4	A1	A2	A3	A4	
Year 2010												
Balahur, Kabadjov and Steinberger (2010)		•	•		•			•		•		Blogs
Das and Bandyopadhyay (2010)		•	•	•	•			•	•			News corpus
Du et al.(2010)	•				•	•				•		Product/Service review
Fu and Wang (2010)		•			•	•				•		News corpus
He (2010)		•		•					•	•		Product review
Hui and Gregory (2010)		•		•	•					•		Blogs
Kechaou, Benammar and Alimi (2010)		•		•	•	•		•				Product review
Khan, A., Baharudin and Khan, K.(2010)		•			•				•	•		Movie reviews
Nishikawa *et al*. (2010)		•	•		•					•		Restaurant reviews
Yan-Yan, Bing and Ting (2010)		•			•				•	•		Product review
Yessenalina, Yue and Cardie (2010)		•			•		•		•			Movie reviews/ Political debate

***Research areas**:* *(R1) Development of linguistic resource, (R2) Sentiment classification, (R3) Opinion summarization*

***Levels of analysis**: (L1) Document level, (L2) Sentence level, (L3) Word (Phrase) level, (L4) Feature-base*

***Analysis approaches**: (A1) Dictionary approach, (A2) Machine learning approach, (A3) Statistical approach, (A4) Semantic approach*

Most of the previous studies are paid attention on the feedback of customer in commercial fields. The commercial field is an attractive field because there are vast amounts of user-generated-contents that spread over the World Wide Web. The data are easily to elicitation via internet resources e.g., weblog, discussion forum, e-mail, social media, etc.

According to Table 2.7 on the *Level of analysis* and the *Analysis approaches*, most of previous worked indicated that they utilized the machine learning and statistical approaches as main process and usually analyzing in subtle level (in Sentence or Word (Phrase) level).

2.5.2 Opinion Mining in Educational field

To the best of our knowledge, there are only few studies were adopted OM in educational filed. The summarization of OM in educational fields in recently year is shown in Table 2.8.

Table 2.8 Previous studies on OM (Educational field).

	Research areas			Levels of analysis				Analysis approaches				
Authors	**R1**	**R2**	**R3**	**L1**	**L2**	**L3**	**L4**	**A1**	**A2**	**A3**	**A4**	**Dataset**
Year 2012												
Leong, Lee and Mak (2012)		•	•		•	•			•			Student's feedbacks (SMS)
Ramadoss and Kannan (2012)		•			•				•			Student feedbacks
Year 2011												
El-Halees (2011)		•	•				•		•			Student discussion on web forum
Jordan (2011)		•		•	•				•	•		Student feedbacks

Table 2.8 Previous studies on OM (Educational field) (continued)

Authors	Research areas			Levels of analysis				Analysis approaches				Dataset
	R1	R2	R3	L1	L2	L3	L4	A1	A2	A3	A4	
Year 2010												
Abd-Elrahman, Andreu and Abbott (2010)		•	•				•			•		Student feedbacks
Kannan and Bielikova (2010)		•	•	•	•				•	•		Educational feedbacks

***Research areas**: (R1) Development of linguistic resource, (R2) Sentiment classification,*
(R3) Opinion summarization

***Levels of analysis**: (L1) Document level, (L2) Sentence level, (L3) Word (Phrase) level, (L4) Feature-base*

***Analysis approaches**: (A1) Dictionary approach, (A2) Machine learning approach,*
(A3) Statistical approach, (A4) Semantic approach

Kannan and Bielikova (2010) proposed a conceptual framework of a system called “The Institution Ecosystem”. This conceptual framework used K-means and Intuitive clustering approach to mining stakeholder’s feedbacks (Employee, People, Parent and Student). Taxonomy from these feedbacks is created. They visualize the data in high dimensional spaces. Pattern and relationships of taxonomy was discovered through the correlation and classification technique.

Abd-Elrahman, Andreu and Abbott (2010) analyzed the data from course evaluation. Manually categorizes are analyzed against with the automatically co-occurrence counting categorizes. Five major elements of the teaching process were defined: 1) Course, 2) Instructor, 3) Assessment, 4) Material, and 5) Delivery. A simple statistical formula called “Teaching Evaluation Index (TEI)” is proposed. TEI compute the ratios of counting data from both manners (Manual and Automatics) into quantitative information. The result indicated that the performance of automatics co-occurrence-base analysis and human manually has strong correlation and correctness.

El-Halees (2011) used OM to evaluate the quality of course. The student's feedback sentences which discussed on web forum were selected as resource. Differ from Abd-Elrahman, Andreu and Abbott (2010) as mentioned above, five major features of teaching were extracted including: 1) Teacher, 2) Content, 3) Exams, 4) Marks, and 5) Books. The three popular machine learning methods: K-nearest, Naïve Bayes and Support Vector Machine were applied to classify feedback. The classifier was classifying feedback into bipolar of opinion (Positive and Negative) following the five pre-defined features and visualizes opinion score as bar graph of each feature in a course.

Ramadoss and Kannan (2012) proposed a teaching evaluation system that collected the feedbacks from students. The purpose system consists of three types of questions: 1) Rating scale question, 2) Multiple choices question, and 3) Short descriptive question. They used OM to analyze the answer of short descriptive question. The explicit features of opinion were extracted from rule-base patterns, while the implicit feature is ignored. The result showed that the rule-base patterns provided the highest rate of precision and recall.

Jordan (2011) explored the hidden dimensions of teaching quality from the student's feedback that questionnaire were not coverage. Text pre-processing techniques (stop-word removing and word stemming) were applied to filter the noise data. Inverse Document Frequency (IDF) and K-means algorithm were used as basic process to analyze and identify the quality of teaching. Principle Component Analysis (PCA) was used to reveal the core component that most students concerned.

The last but not the least, Leong, Lee and Mak (2012) proposed a teaching evaluation system called “SMS Response management System (SMSRS)”. This system is a platform independent web-application. The system allows audience in a class to send their responses and feedback via Short Message Service (SMS). SMSRS deal with the error typing and emotion expression in SMS. The feature and opinion were extracted through rule-base patterns. The exploratory data analysis was used to group each feature into a concept. The concept was visualized and ranked as bar chart and network graph following the terms of frequency and percentage of occurrence. These existing works as mentioned above are compared as shown in Table 2.9.

Table 2.9 Comparison of existing work of OM in educational field

Authors	Approach	Representation	Polarity categorizes	Scoring
Kannan and Bielikova (2010)	- Extraction: Pattern matching (Rule base) - Classification: K-means & Intuitive clustering	- Taxonomy hierarchical - Visualization (high dimensional spaces)	Binary-class (Positive/Negative)	- Count of *word occurrence*
Abd-Elrahman, Andreu and Abbott (2010)	- Extraction: Manual/Automatic word counting - Classification: Matching with keyword list	5 categories (pre-defined from comments) *1) Course 2) Instructor 3) Assessment 4) Material and 5) Delivery*	Binary-class (Positive/Negative)	- Count of *word occurrence :TEI index (ratio of Pos/Neg word)*

Table 2.9 Comparison of existing work of OM in educational field (continued)

Authors	Approach	Representation	Polarity categorizes	Scoring
El-Halees (2011)	- Extraction: Association rule mining - Classification: Machine learning (NB, kNN, SVM) with keyword list	5 categories (pre-defined from comments) *1) Contain 2) Teacher 3) Exams 4) Marks and 5) Books* -Visualization (Bar chart)	Multi-classes (Positive/Negative/ Neural)	Count of *word occurrence (% of Pos/Neg word)*
Ramadoss and Kannan (2012)	- Extraction : Pattern matching (Rule base) - Classification : Matching with keyword list	15 categories (pre-defined from close-end questions)	Binary-class (Positive/Negative)	Count of *word occurrence*
Jordan (2011)	- Extraction : TF-IDF, PCA→SVD - Classification : K-Means	3 majors categories with 11 sub-categories (pre-defined from previous studies)	Multi-classes (Positive/Negative/ Neural)	Count of *word occurrence*
Leong, Lee and Mak (2012)	- Extraction : Pattern matching (rule base) - Classification : Exploratory data analysis	Top 4 categories *1) Lecture 2) Pace 3) Jokes and 4) Teacher* (ranking follows % of word occurrence) -Visualization (Network graph)	Binary-class (Positive/Negative)	Count of linking between word on graph

Table 2.9 revealed that the sentiment classification and opinion summarization are attracted research area in educational field. The machine learning and statistics approach are the most popular processes to extract and classify data. Analyzing was performed in sentence level. Data usually categorize into binary classes.

Several numbers of teaching characteristics are predefined and represented based on the quantity of observed data (counting of word occurrence).

2.5.3 Opinion Mining with Thai language

Sriphaew, Takamura and Okumura (2009) described the potential process for an opinion mining to work on some other language by applying the existing methods with some language-specific information, labeled of the target languages and machine translation services.

For subjective/objective identification, the simplest way to classify whether the given text is subjective or objective is to use the terms or structure of text as cues for identification. For example, a sentence that contains the term which express the feeling such as “I think that” or “I feel that”, is usually subjective sentence, or texts that are under the topic of “review” or “comment” can be assumed as an opinionated texts. To apply this for Thai, the lexical cues can directly defined in order to detect the subjective sentences from the objective ones, but the pre-process of word segmentation and sentence boundary detection must be applied beforehand.

For sentiment classification, several techniques have been developed to find out the semantic orientation of the opinion. The orientation can be classified into three classes named “positive”, “negative” and “neutral”. Sentiment classification can be performed in different levels of granularity of text, i.e., word, phrase, sentence, paragraph or document. Most of the techniques are based on machine learning approach where the labeled data is provided for learning the classification model. This is a main obstacle to the resource-scarce language such as Thai since such labeled data is not available and it consumes considerable time and large human efforts if we want to construct one. However, some techniques for cross-lingual analysis can make it feasible by using machine translation services as tools to translate the English labeled corpus to the other target languages, then applying learning technique for cross-learning on the corpus.

In additional, extracting the features of the entities or topics are extracted with their underlying opinions. A feature or aspect can be an attribute, component or a function of an entity. For example, the picture quality, size and weight can be the features of a camera. To implement this task, mining technique is applied to extract the features or aspects of the entities by finding the noun phrases that are usually occurred with the terms that express the opinion.

In the last decade, several Thai researchers attempt to develop an opinion mining process that deals with Thai language. These previous work have characteristics which correspond with the description by Sriphaew *et. al.*(2009). However, it is experiments in commercial fields. List of previous work as follows:

Haruechaiyasak, Kongthon, Palingoon and Sangkeettrakarn (2010) constructed Thai language resource for feature based opinion mining. These lexicons were designed to distinguish lexicons into two types: Domain-dependent and Domain-independent lexicons. The domain-dependent starts by setting the domain scope such as digital camera. The next step is to design a set of features (main-features) and sub-features associated with the given domain. Finally, the polar words lexicon is constructed. These words represent either positive or negative views on features. The other type of lexicon is domain-independent. It consists of with six different types of words including: 1) Particles (ending word which make politeness sentence), 2) Negative words, 3) Degree words, 4) Auxiliary verbs, 5) Prepositions, and

6) Stop words. To collect more lexicons, linguistics patterns called “Dual pattern extraction” is constructed to extract more features and polar word from the untagged corpus.

Thumrongluck and Mongkolnavin (2011) developed an automatics system to summarize Thai consumer product reviews. This system extract feature of product by Term Frequency-Inverse Class Frequency (TFICF), an extended of TFIDF model which consider co-occurrence between terms and classes. To determine their polarity, the initial words list (seed words) is created, Then the related words is expanded with WordNet. The Reverse-Distance-Weight (RDW) is a weighting score technique for the opinion word term position that surrounds the feature word. The summation of weight score is used to determine polarity direction.

Kongthon, Haruechaiyasak, Sangkeettrakarn, Palingoon and Wunnasri (2011) extended the previous works of Haruechaiyasak *et. al.*(2010). The lexicon about hotel reviews is used to develop an opinion mining system called “HotelOpinion”. This system is a feature-based level that can compare between difference hotels. Their polarities of each feature are obtained by summation of total number of positive and negative words occurrence.

Sukhum, Nitsuwat and Haruechaiyasak (2011) studies to identify the opinion sentence in political news. The performance of three well-known machine learning techniques: k-Nearest neighbors, Naïve Bayes, and Support Vector Machine against with several types of text features are compared. Experiments are conducted at sentence level. The experimental results indicated that Naïve Bayes classifier with prior-knowledge base features (Clue words, Keywords, and Name Entity) given the overall performance (Precision, Recall, and F-measure) higher than 0.80.

Pongtanu, Rungwarawut, Arch-Int, N. and Arch-Int, S. (2012) classified the customer satisfaction. The experiment performed at document level. The two machine learning techniques: Decision tree and Naïve Bayes are compared against with the term presence model of keywords. The results indicated that Decision tree delivered an average of accuracy at 95.50%, while Naïve Bayes delivered an average of accuracy at 95.33%.

Phawattanakul and Luenam (2013) mined the suggestion of Thai television program reviews. The aim of this work is similar to the subjective/objective identification tasks. The process of this works consists of two parts: 1) constructing knowledge based and 2) classifying each suggestion in the reviews as either "suggestion" or "non-suggestion" sentence. In first part, their knowledge base consists of four types of words including: 1) Domain-dependency (DW), 2) Part-Of-Speech (POS), 3) Domain wordlists (DW), and 4) Association wordlist (AW). The first two are obtained with Thai text-processing application. The third word type is considered and selected by expert domain, while the fourth word type is obtained by association rules mining. To classify, this knowledge base is used to extract and tag the important words in sentence. Combination of several word types are generated and represented in TF-IDF model. The Support Vector Machine is used as classifier. The result indicated that SVM with the feature that comprise the word, POS, and AW tagging given the better performance (Precision is 0.83, Recall is 0.94, and F-measure is 0.88).

The last but not the least, Apisuwankun and Mongkolnavin (2013) extend the previous work of Thumrongluck and Mongkolnavin (2011). This work aims to identify the opinion strength score. A technique called "Human coder subjective judgment" that derived from Thelwall *et al.* (2010) is used. This technique uses expert to assign the strength score of individual word lists of bipolar in 5 scales (Positive: +1 to +5, Negative: -1 to -5). This score uses with some syntactic rules of word order. For example, a word obtained 4 strength score of positive, if there is a negative word appeared in front of them, the polarity will be inverted to negative. The training dataset is generated from short sentence with these rules by fixed the strength score as target class. Association rule mining is implemented to obtain the significant rules. The opinion strength score obtained by summation of the strength score of overall sentence.

According to the previous work, the machine learning technique showed the significant of performance. However, the human effort is still required. This work aims to develop a system which uses the hybrid approach that combines the machine learning, statistical approach and semantic approach. The machine learning and statistical approach provide the significant of performance, while the semantics approach makes more accuracy of classification similar to using human manually. Moreover, this work focuses in the educational domain. Thai student's feedback is analyzed in sentence level and represented as feature based level (fine-grain analysis). This proposed system provides the benefit to indicate the quality of individual teaching based on the good teaching characteristics categories.

2.6 Summary

According to the related theoretical and previous studies, there are only few works, which adopted OM in the educational data. Most of the previous work of OM is developed on European language. To the best of our knowledge, there is no implementation of OM in order to analyze and extract information from educational feedback that expressed in Thai Language.

Firstly, the social research technique is implemented to identify the component of good teaching characteristics that correspond with Thai educational context. Then study about adapt OM approach with Thai student's feedback and design a framework to extract information form Thai student feedbacks.

Secondly, to develop a system that can be analyzed and extracted useful information about teaching process from Thai student’s feedback. The process of analysis is based on the opinion mining steps. Several instruments are implemented e.g., Thai language applications, Linguistics resources, the machine learning technique, statistical technique and semantics computational technique are combined in order to develop this proposed system.

Finally, the useful information from this proposed framework are stored in database. This information can be used to indicate the strength or weakness in teaching process of individual teacher.

The rest of this dissertation is organized as follows: developing process of a knowledge extraction system from online teaching evaluation system is described in the Chapter 3. Chapter 4 explained the experiments and results of this study, the conclusion and future work is presented in the Chapter 5.

CHAPTER 3

RESEARCH METHODOLOGY

This chapter presents the methodology to develop a framework to extract knowledge and useful information from online teaching evaluation. Methodology of this study is described as follows:

3.1 Methodology

3.1.1 Study of related theory and existing work

3.1.2 Framework modeling and development

3.1.3 Framework evaluation

3.2 Population and Samples

3.3 Research Instruments

3.3.1 Design and development instruments

3.3.2 Instruments for evaluation

3.4 Data Collection and Analysis

3.1 Methodology

This study is an "Applied research" which aims to develop a framework for extracting knowledge and useful information about teaching process from Thai student's feedback. The Software Development Life Cycle process (SDLC) was applied as the development process. Data mining and statistical approaches were used as a core process of knowledge extraction. Appropriate information and knowledge for improving teaching process are stored and represented via ontology model. The conceptual framework of research methodology is depicted in Figure 3.1.

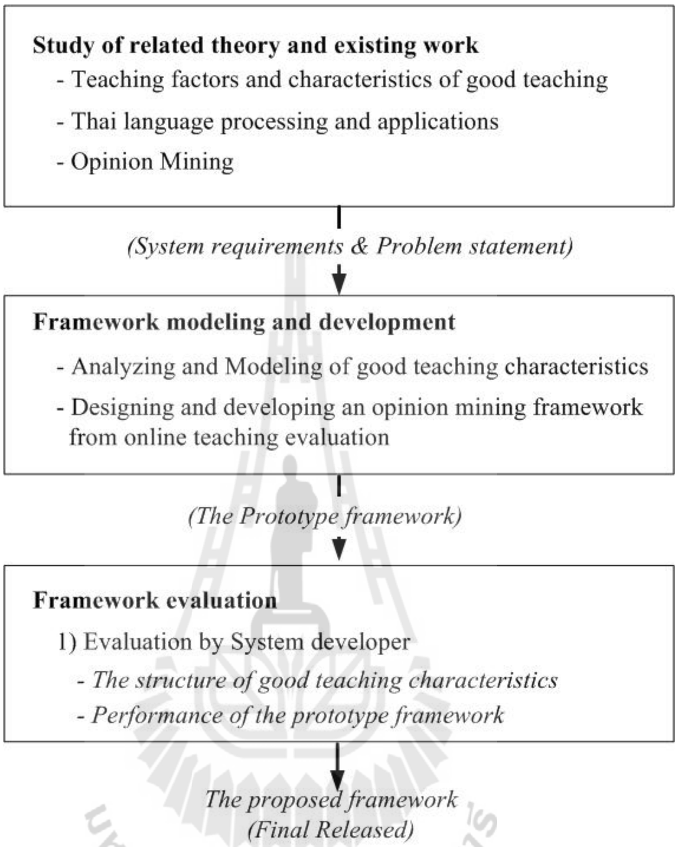


Figure 3.1 Conceptual framework of research methodology

3.1.1 Study related theory and existing work

The purpose of this step is to study theory that related with developing process of an opinion mining framework for online teaching evaluation. Three main theories are studied consisting of 1) Teaching factors and characteristics of good teaching, 2) Thai language processing and applications, and 3) Opinion Mining. Summary of these studies are described as follows:

1. Teaching factors and characteristics of good teaching

This study aims to analyze and identify whether factors and characteristics of teaching influence to the quality of teaching process. As described in previous chapter (Chapter 2: Table 2.1), several characteristics of good teaching are identified by educationists and researchers. These factors can be roughly categorized into six groups as follows: Knowledge, Preparation, Teaching technique, Assessment, Material and Personality.

Several characteristics of good teaching are identified on their different educational context. To identify the teaching characteristics which are appropriate for Thai educational context. Summary of these good teaching characteristics and social science research process is applied to identify the good teaching characteristics in Thai educational context. The process of modeling and refining are explained in the framework modeling and development section (Section 3.1.2).

2. Thai language processing

Summary of problems of Thai language and their application are described as follows:

1) Thai language does not have the punctuation marks, such as space or full stop to identify word or sentence boundary. Thai language also does not have the capital letter.

2) The ambiguous of word meaning when appears in different position in sentence or in different context.

3) There are special word genres, such as Name Entity, Transliteration word or Phrase from word compounding.

4) Flexible of grammatical structure, e.g., some component of sentence (subject or object) can be omitted.

Additionally, there is the effect of "*Electronics grammar*" e.g., the words, which are written follow speaking sound, repeating of vowel or characters, using the group of symbols to represent their feeling called "emotion", etc. These special characteristics of written forms usually found in modern communication system, e.g., Short-Messaging-Service (SMS), Web Board, Chats room, Web Blog, Social media (e.g., Facebook, Twitter, etc.), and online teaching evaluation.

To overcome these problems, Word segmentation and Part-Of-Speech tagging application are prerequisite process. For Thai language, there are some available application for Thai word segmentation such as "SWATH", "LibThai", "KUcut", "LexTo", and "TLexs". Application for Part-Of-Speech tagging, e.g., "SWATH", "KUcut", "Jitar (with NAiST model)", and "OpenNLP" are presented. There are other efforts to adopt the software as services via internet system such as "Thaisemantics.org" and "KU Wordcut Demo". There are two popular Part-Of-Speech tagsets called "ORCHID tagset" and "NAiST tagset".

Beside, application for text pre-processing, the linguistics resource and dictionaries are used. The most popular referring linguistics resource is WordNet. It is a general purpose linguistics resource with well-formed of structure. The semantics similarity techniques based on WordNet is presented to solve the ambiguity problem. The SentiWordNet is used as initial of opinion score. A Thai-English dictionary called "LEXiTRON" would be used as supplementary linguistics resource to link between Thai and English language.

3. Opinion Mining

The aim of Opinion Mining (OM) is an attempt to take advantage from vast amounts of user's feedback by analyzing and extracting useful information with sophisticated processes. The research areas of OM can be divided into three areas including: 1) Development of linguistic resource, 2) Sentiment classification, and 3) Opinion summarization.

The first area is "Development of linguistic resource". This area aims to develop a lexicon with word's polarity. Bosco, Patti and Bolioli (2015) stated that there are three main steps to develop a corpus: collection, annotation and analysis. Each of them is strongly influenced by the others. For instance, the analysis and exploitation of a corpus can reveal limits of the annotation or data sampling, which can be respectively addressed by improving annotation and collecting more adequate data. In order to automatically develop linguistic resource, several researchers used sophisticated machine learning technique to extract and identify important words from several available corpuses.

The second area is "Sentiment classification". This area is a popularly studied area that most researchers were paid attention. This area involved with Identification and Classification steps. According to Esuli and Sebastiani (2005), steps of Sentiment classification can be explained as three specific subtasks: 1) Determining subjectivity, 2) Determining polarity, and 3) Determining strength of polarity.

The last one is "Opinion summarization". It expected to allow all possible reviews to be efficiently utilized by users. Given multiple reviews, the text summarizer outputs consist of ordered sentences. A typical summary can be considered as multi-document summarization. Existing summarizers focus on organizing sentences to include important information in the given document into a summary under some size limitation. Unfortunately, most of these summarizers completely ignore coherence of the summary, which improves reader's comprehension as reported (Nishikawa, Hasegawa, Matsuo and Kikui, 2010).

Although, there are popular used of Opinion Mining however it only spread over in commercial field. In the last decades, only few work study on educational data, e.g., Kannan and Bielikova (2010), Abd-Elrahman, Andreu and Abbott (2010), Jordan (2011), El-Halees (2011), Ramadoss and Kannan (2012), and Leong, Lee and Mak (2012). These previous works on educational data, the machine learning and statistical approaches were used as main process to mine these opinion passages. Analyzing is operated on the feature set of interest object and analyze in subtle level.

According to the fundamental theories as mentioned above, designing and developing of an opinion mining framework for online teaching evaluation are presented in the next section.

3.1.2 Framework modeling and development

In this section, an opinion mining framework for online teaching evaluation is presented. This proposed framework was modeled and developed correspond to the objective of this study consists of three important issues as follow:

1. Analyzing and modeling of good teaching characteristics
2. Design and develop an opinion mining framework for online teaching evaluation

The first issue is answered the objective of studies that "To identify the component of good teaching characteristics that corresponds with Thai educational context". The last two issues are answered the objective of this studies that "To design and develop an efficient opinion mining framework for analyze student feedback from online teaching evaluation corresponds to good teaching characteristics".

1. Analyzing and modeling of good teaching characteristics

Several previous works, as discussed in Chapter 2, defined several characteristics of good teaching. To refine and select items of good teaching characteristics, which are appropriated and corresponded with Thai educational context, the social research approach and Structural Equation Modeling (SEM) technique are applied. SEM is a general term that describes a large number of statistical models which are used to test and validate substantive theories with empirical data. This technique combines a measurement model (or Confirmatory Factor Analysis: CFA) and structural model into a simultaneous statistical test. The patterns of relationships between factors (latent variables) that obtain from factor analysis process are constructed based on the study of educational theory (Lei and Wu, 2007; Hoe, 2008; Jacobson *et al.*, 2009). The process to analyze and model of good teaching characteristics can be described as follows:

1.1. Population and Samples

The population is separated into two groups consisting of 1) Faculty: the full time instructors at Suranaree University of Technology (SUT), Thailand, and 2) Students: the learners who are studying undergraduate level at SUT. The table for determining sample size (Krejcie and Morgan, 1970) was used to determine of sample size. The total amount of sample units consisting of 97 SUT faculty and 474 students were selected with the simple random sampling technique.

1.2. Development of Research Instruments and Quality testing

1) Review the educational textbooks, academic papers and results of previous work that related to the teaching and learning process, and then synthesizing the characteristics of the teaching process and good teaching characteristics.

2) Synthesizing the list of good teaching characteristics items (reviewing of literature as mentioned in Chapter 2). The Likert scale questionnaire which consists of 66 items based on previous studies were constructed (Appendix A). Initially, these questionnaire items are categorized into six component of good teaching. The numbers of items of each component as follows: Knowledge (4 items), Preparation (4 items), Teaching technique (28 items), Assessment (8 items), Materials (4 items), and Personality (18 items).

3) The questionnaire was designed for answering two questions including: 1) these question items are the good teaching characteristics that correspond to Thailand's learning context; and 2) these good teaching characteristic items are easy to observe by students and/or easy to practice by teachers.

4) Quality testing of research instrument, The Index of Item Objective Congruence (IOC) was computed to indicate validity of the question item with objective of surveying. The Cronbach's α-coefficient (Cronbach, 1951) is used to indicate the reliability of overall questionnaire. This questionnaire was try-out with 30 students and 10 teacher of Suranaree University of Technology. The question items are obtained IOC scores between 0.88 and 1.00, which above the minimum threshold (at 0.50). In aspect of reliability of questionnaire, these questionnaires obtained a high reliability rate at 0.983.

1.3. Data analysis

The Structural Equation Modeling (SEM) is used to confirm the structure of good teaching characteristics model. The phase of data analysis is separated into two stages: (1) Identifying and selecting the good teaching characteristics that correspond with teaching and learning process and (2) Developing the good teaching characteristics model. The process and statistical methods that are used to analyze data can be described as follows:

1) Identifying and selecting items: the Index of Item Objective Congruence method is adopted to analyze the closed-end questions. The items that obtained the IOC score higher than the threshold value (at 0.50) will be identified as characteristics of good teaching where the teacher and student are concerned.

2) Developing a good teaching characteristics model: This phase consists of two stages; First stage is categorization the questionnaire items by utilized the Exploratory Factor Analysis (EFA). This stage providing and confirming the properly group of each questionnaire item and new terminology of good teaching component were redefined. Moreover, the result of EFA produces new latent variables which are used in SEM model, and Second stage, the second order Confirmatory Factor Analysis (CFA) is computed to indicate the fitness of the model (Overall structure of relationship between observed variable and latent variables) with empirical data. The principal factors and factor loading value that affect the teaching and learning process are presented as the final model.

Structure of good teaching characteristics model and statistical indicator results are presented in Chapter 4.

2. Design and development of an opinion mining framework for online teaching evaluation

Principal contribution of this study is to design and develop a framework that can extract knowledge to indicate the strength or weakness of teaching process from student's feedback. The Opinion Mining (OM) is used as core process of analyzing. Reviewing of literatures in previous chapter (in Chapter 2: Opinion mining) is used as fundamental theory to design and develop this proposed framework. Three main modules are; 1) *Linguistic pre-processing*, 2) *Opinion analysis*, and 3) *Aggregation and Visualization*. The architecture of proposed framework is shown in Figure 3.2.

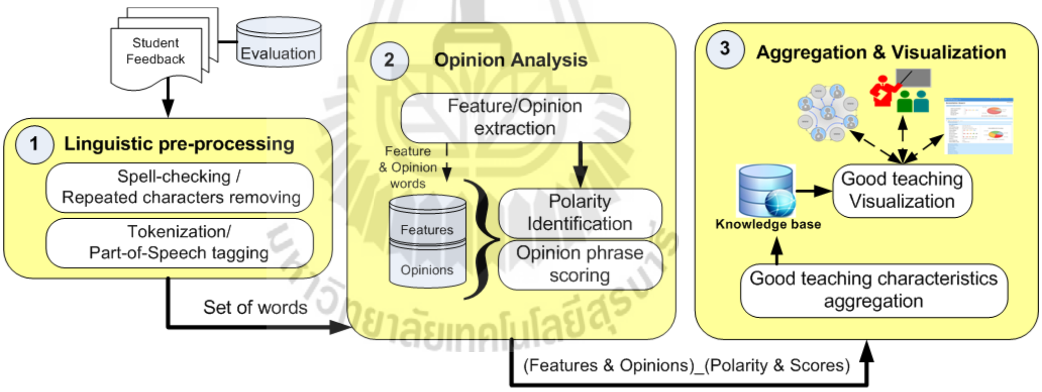


Figure 3.2 The architecture of the proposed system

This framework retrieved free format text paragraph of student's feedback from the database of online teaching evaluation system. These paragraphs are passed through the proposed system. The function of each module and processing step can be described as follows:

1. Linguistic pre-processing

This first module can be considered as data cleaning and preparing process. This module consists of two basic tasks including: 1) Spell-checking/Repeated characters removing and 2) Tokenization/Part-Of-Speech tagging. Spell-checking/Repeated characters removing task is to clean unwanted data in student feedback paragraph by searching and replacing the redundant of characters. Also, remove all symbols with regular expression. After that, in Tokenization/Part-Of-Speech tagging, student feedback was segmented by using *LexTo* application. Part-Of-Speech of each word was tagged by *ApacheNLP* application with *ORCHID* tagsets. The final result of this module is set of word tokens with tagged Part-Of-Speech of each word.

2. Opinion Analysis

This is the main computational module which is used to obtain the opinion score from student feedback. Esuli and Sebastiani (2005, 2006) defined the steps of sentiment classification as three specific subtasks, which are 1) Determining subjectivity, 2) Determining polarity, and 3) Determining strength of polarity. In this work, three sub-modules of opinion mining are: 1) Feature/Opinion extraction, 2) Polarity identification, and 3) Opinion phrase scoring. Processes of each sub-module are described as follows:

2.1 Feature/Opinion extraction

This is the first task of proposed framework. It aims to decide which word in tokens list are “Feature” or “Opinion” words. In previous studies, identification and extraction tasks are usually rely on integration of the rule-base with computational method e.g., Rule-based pattern with Likelihood score (Yi *et al*., 2003), Rule-based pattern with PMI (Popescu and Etzioni, 2005), Class Association Rule (Hu and Liu, 2006), Double Propagation (a word-dependency) (Qiu *et al*., 2009), Double Propagation and HITs algorithm (Zhang *et al.*, 2010), Rule-based pattern with K-means clustering (Liu *et al.*, 2013), etc.

The rule-based pattern approach has high precision. Thus, it is usually used as extraction process in most of previous researches. In order to obtain accurate and coverage of syntactic rules pattern, the linguistics knowledge and higher workload of domain expert was required. To overcome the feature and opinion word extraction problem, this work considers extraction problem as a classification task. The machine learning approach is used as main process of this module.

Structure of this feature/opinion extraction module is divided into two stages consist of (*I) Fragment classification* and (*II) Fragment summarization*. Overall process of this module is shown in Figure 3.3.

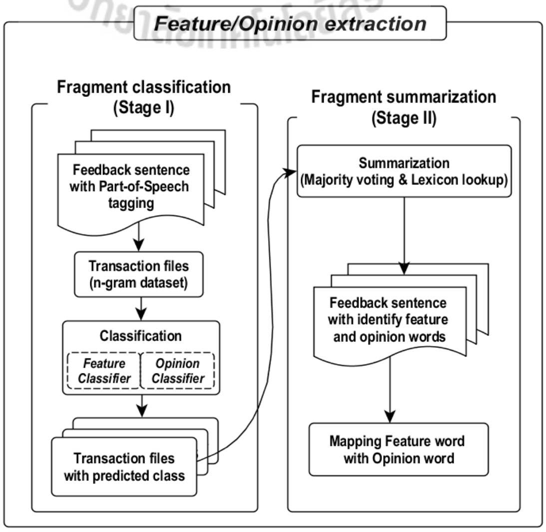


Figure 3.3 The process of the feature/opinion extraction module

Fragment classification (Stage I)

The initial data of this stage are feedback sentence with their Part-Of-Speech that obtained from previous module: Linguistic Pre-processing (as shown in Figure 3.2). The vital technique of this stage is the two classifiers with transaction files. Transaction file is the *n*-gram dataset. For classification, transaction file and classifiers are generated as follows:

1) Transaction file generated from feedback sentence, the *n*-gram technique is widely used in the text mining. The *n*-grams are used as a process to generate a dataset for training the classifier. According to the experiment of Hu and Liu (2006), the optimal size of *n*-grams is 3 word sequences. The example of a 3-gram dataset which is generated from a sentence is shown in Figure 3.4.

2) Those 3-gram data records are arranged and stored in a transaction file. The common structure of this transaction file consists of 6 variables including: the first three variables are 3-gram words sequentially (*TEXT1-TEXT3*) and the last three variables are Part-Of-Speech of each word (*POS1-POS3*) (Hu and Liu, 2006). To train the classifier, two copies of this transaction file are generated. These two transaction files are "feature" and "opinion" dataset. They have different target class variables (*FCLASS* and *OCLASS*). The *FCLASS* is target class for feature dataset which is used to train the feature classifier. Likewise, the opinion dataset uses the *OCLASS* as target class for training the opinion classifier.

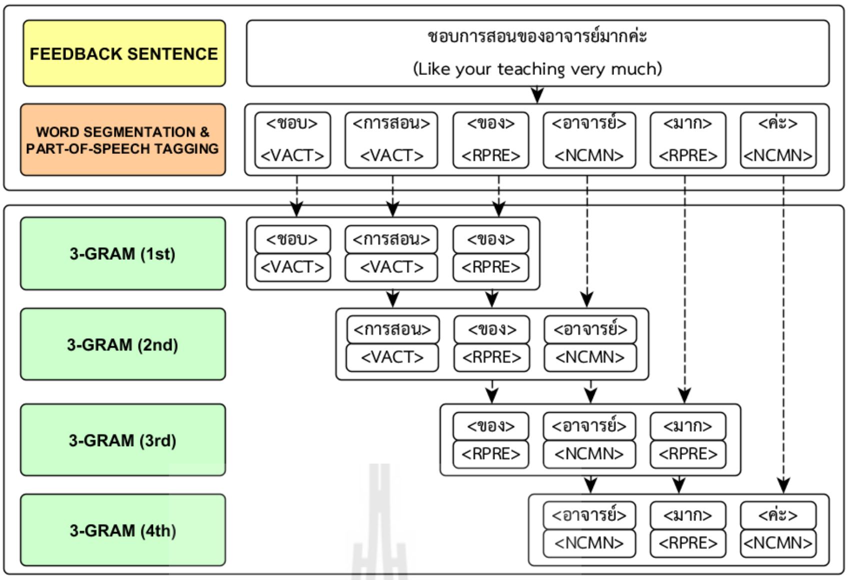


Figure 3.4 Generating of *n*-gram data records

Both of target class variables consist of eight pre-defined categories. These categories consist of 1) “*000*”, 2) “*001*”, 3) “*010*”, 4) “*011*”, 5) “*100*”, 6) “*101*”, 7) “*110*”, and 8) “*111*”. The values of class variables are adapted from “*IO*” encoding method (Breck *et al.*, 2007). The objective of each number (“*0*” or “*1*”) is any bits that have “*1*” value indicate that the word at this position is a candidate feature word in *FCLASS* transaction file; whereas “*0*” means this word is not identified as a feature word. Similarly, these “*0*” and “*1*” used to identify an opinion word position in *OCLASS* transaction file. To prepare these training datasets, Thai native speaker is asked to assign the categories of class in each *n*-gram data record. An example structure of the transaction file is illustrated in Figure 3.5.

3) Obtaining the best two classifiers, the machine learning is trained to identify whether word position in *n*-gram fragment of feedback sentence. The four machine learning techniques including: 1) Naïve Bayes (NB), 2) Support Vector Machine (SVM), 3) K-nearest neighbor (KNN), and 4) Classification Based on

Associations (CBA) (Hu and Liu, 2006; Liu *et al.*, 1998), are trained with feature and opinion datasets in order to obtain the best classifier. The WEKA (The Waikato Environment for Knowledge Analysis) (Hall *et al.*, 2009) with their default parameters and 10-fold cross-validations are used to trained and tested those classifiers. Finally, the best two classifiers (*Feature classifier* and *Opinion classifier*) are selected for classifying each *n*-gram data record into 8 categorizes as mentioned above. The performances of classifiers are presented in Chapter 4. Then, these classification results are forwarded as data input to the next stage II (the fragment summarization stage).

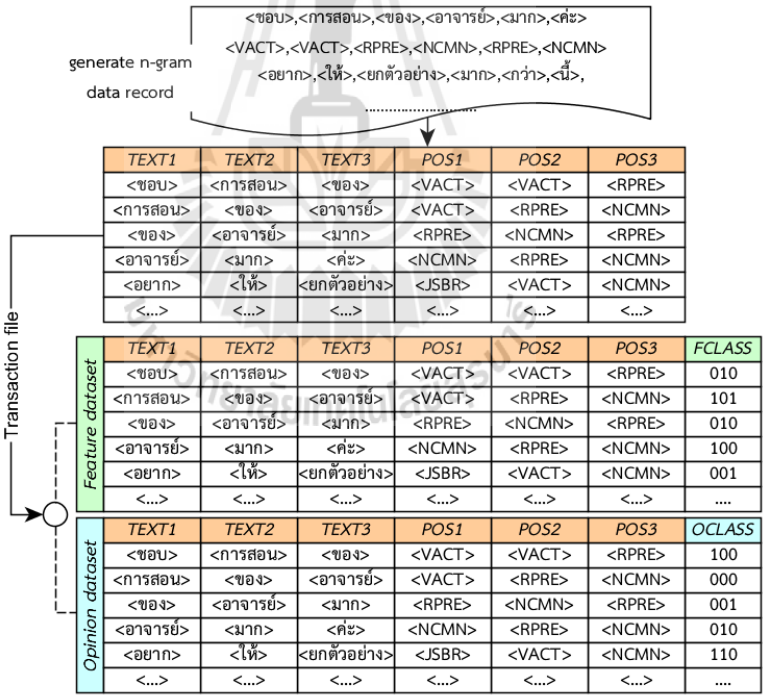


Figure 3.5 A transaction file with classes tagging

Fragment summarization (Stage II)

According to the result of Stage I, those results are a part of the original feedback sentence which breaks down into *n*-gram data records. To obtain the complete results of extracting feature and opinion words of these sentences. This stage utilized the simple technique called "*Majority voting*" which is used to decide whether word in the overlapping position should be assigned as "*0*" or "*1*".

1) The process of n-gram majority voting is shown in Algorithm 3.1.

Algorithm 3.1: *N-gram majority voting*

Input : - M is Total number of n-gram data records of a sentence

- C is Set of classification result of *n*-gram data record (predicted by classifier)
- k is Size of n-gram (k = 3)
- BC_x is Counter of "0" and "1" votes

Output : - SC is fragment merged results of a sentence

Steps :

1. Set i = 1, $SC = C_i$
2. Set $BC_0[k+M-1] = BC_1[k+M-1]$={*NULL*}
3. Do while $i < M$ *### Counting "0/1" step*

    $C_i = C_i << (M-i), i = (i+1)$

    For $j= i, j < (i+k), j++$

    Select case $\{C_i[j]\}$

    Case 0 -> $BC_0[j]$++

    Case 1 -> $BC_1[j]$++

    Loop

  Loop

4. For $j = i, j < (k + M - 1), j$++ ### *Decision step*

 If $BC_0[j] = NULL$ and $BC_1[j]$!= $NULL$ Then $SC[j]=1$

 If $BC_0[j]$!= $NULL$ and $BC_1[j] = NULL$ Then $SC[j]=0$

 If $BC_0[j] <= BC_1[j]$ Then $SC[j] = 1$

 If $BC_0[j] > BC_1[j]$ Then $SC[j] = 0$

 Loop

5. Return *SC*

This n-gram majority voting process as illustrated above can also be simple as depicted in Figure 3.6. Moreover, the lexicon lookup with fuzzy string matching are implemented to indicate the position of stop words and well-known words as feature or opinion word. Sukhum *et al.* (2011) suggested that list of keywords is a technique which give benefit for improving the efficient of a system that deal with natural language.

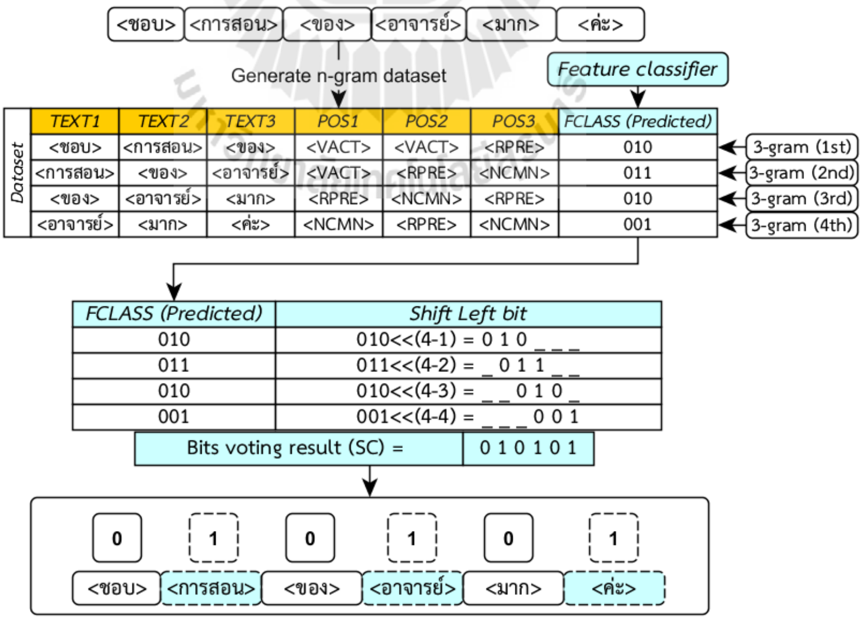


Figure 3.6 N-gram majority voting process

2) A string similarity method called “*Jaro-Winkler*” (Cohen *et al.*, 2003) is used to compare between the stop word list (Kesorn, 2013) (lexicon lookup) and each word in a feedback sentence. The threshold value of similarity score is set at 0.90. If the similarity scores more than the threshold, it would be fixed as “*0*”. This process is shown in Figure 3.7.

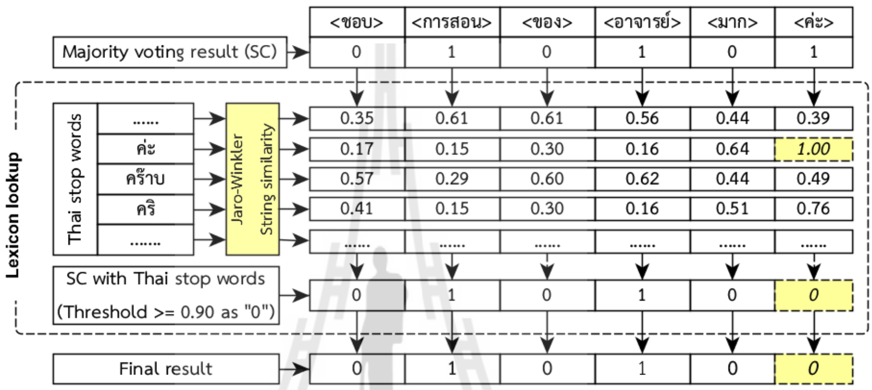


Figure 3.7 String matching with Lexicon lookup

3) Finally, the final output of these steps is the feedback sentence which having word position indicator of feature word and opinion word. For identifying the opinion words, the same process is repeated with the opinion classifier. The feature and opinion words are obtained by extract the word that have “*1*” indicators.

4) There are several features and opinion words were extracted. These words were mapped based on highest of Pointwise Mutual Information (PMI) score. Finally, this extraction can be reduced as a feature word with several of opinion words. The evaluation result of the Feature/Opinion extraction sub-module is presented in Chapter 4.

2.2 Polarity identification

After the opinion words are obtained, a sub-module called "Polarity identification" is performed. The aim of this sub-module is to categorize the polarity of the opinion word into 3 categories. The main technique of this process is slightly differs from previous sub-module. The machine learning technique is used as a core process without using the majority voting in decision step. The three machine learning classifiers are trained with this *n*-gram data set. Their performances are compared, and then the best classifier was selected to be the polarity classifier. Process of polarity identification sub-module can be depicted in Figure 3.8.

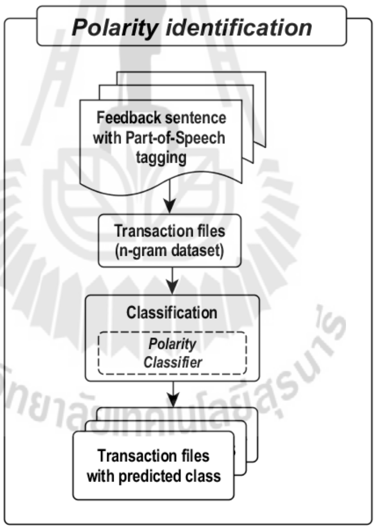
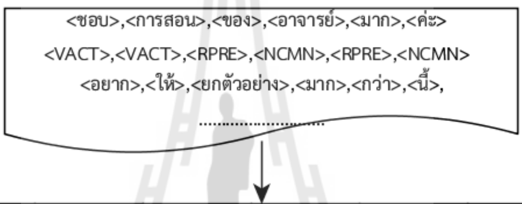


Figure 3.8 Process of the polarity identification module

In this module the machine learning was trained as follows:

1) Generating the training dataset: the dataset based on n-gram are generated. This training data set consists of simple structure similar to previous training dataset. It consists of 6 variables with 1 target class variable.

The 6 variables including: the first three variables (*TEXT1-TEXT3*) are the word sequence from student feedback sentence. The last three variables (*POS1-POS3*) are the Part-Of-Speech of each word in sequence. The target class is different from previous training dataset (in Feature/Opinion extraction module). It consists of 3 categorizes that are "*Positive*", "*Negative*", and "*Neutral*". To prepare these training datasets, Thai native speaker is asked to assign the categories of class in each *n*-gram data record. The example structure of this dataset is illustrated in Figure 3.9.



Polarity dataset

TEXT1	*TEXT2*	*TEXT3*	*POS1*	*POS2*	*POS3*	*CLASS*
<ชอบ>	<การสอน>	<ของ>	<VACT>	<VACT>	<RPRE>	Positive
<การสอน>	<ของ>	<อาจารย์>	<VACT>	<RPRE>	<NCMN>	Neutral
<ของ>	<อาจารย์>	<มาก>	<RPRE>	<NCMN>	<RPRE>	Positive
<อาจารย์>	<มาก>	<ค่ะ>	<NCMN>	<RPRE>	<NCMN>	Positive
<อยาก>	<ให้>	<ยกตัวอย่าง>	<JSBR>	<VACT>	<NCMN>	Negative
<...>	<...>	<...>	<...>	<...>	<...>	....

Figure 3.9 Polarity identification training dataset

2) The WEKA application is used to model the three classifiers called 1) Naïve Bayes (NB), 2) Support Vector Machine (SVM), and 3) Decision Tree (DT). The WEKA default parameters were configured, and 10-fold cross-validations method is used to train and test those classifiers. The best classifier is selected as the polarity classifier. Similar to previous module (Feature/Opinion extraction), the string matching technique with the known polarity word lists (e.g. "However", "But", "Should", "Needs", "Best", etc.) are used to fixed their polarity.

3) To identify their polarity, the context of opinion word that obtained from previous module is used as *n*-gram data record. There are 4 rules to arrange these words tokenize into the form of *n*-gram data record.

- If an opinion word has other words on both left and right side, the opinion word is set as *TEXT2*, while the left word and the right word is set as *TEXT1* and *TEXT3*, respectively.

- If an opinion words only have the other words on the right side, the opinion word is set as *TEXT1*, and the next two consecutive words are set as *TEXT2* and *TEXT3*, respectively.

- If an opinion word only has the words on the left side, then the opinion word is set as *TEXT3*, while the previous two words are set as *TEXT1* and *TEXT2*, respectively.

- If the size of *n*-gram is shorter than 3, the opinion word is set as *TEXT2*. The other variables are replaced with Blank space and set their Part-Of-Speech as punctuation ("PUNC").

Then this *n*-gram data record is used to predict their polarity with the best classifier as mentioned above.

4) Finally, a feature word is mapped with several opinion words. With different polarity of several opinion word, a context-dependent rules list which proposed by Romanyshyn (2013) is used to aggregate several polarity with same feature word. The evaluation result of the polarity identification sub-module is presented in Chapter 4.

2.3 Opinion phrase scoring

This stage aims to estimate strength of opinion in word level. These scores would be used to summarize as opinion score according to the good teaching characteristic to indicate performance of individual teacher in teaching. The process of this sub-module is shown in Figure 3.10.

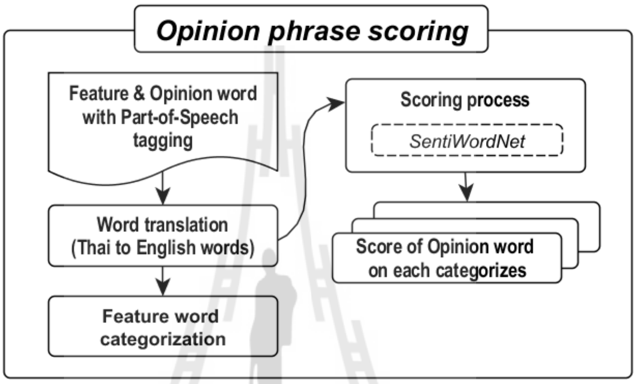


Figure 3.10 The process of the opinion phrase scoring module

This module consists of two main sub-modules including: 1) Feature word categorization and 2) Scoring process. First sub-module can be explained as follows:

Feature word categorization

Step 1) Word translation: After, the feature and opinion word were obtained, the LEXiTRON Thai to English dictionary is used as word translation. The ORCHID Part-of Speech tagset (47 tags) of opinion word are mapped to WordNet tagset (4 tags) as follows.

- The Noun (e.g. NPRP, NCNM, etc), Pronoun (e.g. PPRS, PDMN, etc.), Definite determiner (e.g. DDAN, DDAC, etc.), Unit classifier (e.g.

CNIT, CLTV, etc.), Prefix and Ending (e.g. FIXN, EAFF, etc.) are mapped as "*n*" tags.

- The Verb (e.g. VACT, VSTA, etc.), Pre-verb auxiliary (e.g. XVBM, XVMM, etc.) are mapped as "*v*" tags.

- The Adverb and Adjective (e.g. ADVN, ADVI, etc.) are mapped as "*a*" tags.

- The Conjunction, Preposition and Interjection (e.g. JCRG, JCMP, JSBR, RPRE, INT, etc.) are mapped as "*r*" tags.

Step 2) Categorize Feature word: this process attempts to categorize the feature word into the appropriate category of good teaching characteristics. Several semantic similarities via WordNet are computed with this feature word. A feature word would be assigned as member of a category which having maximum count of semantic similarity. The seed words (keywords of each categorize) are used to compute semantic similarity with the feature word. For example, Let the word "อธิบาย" (Explain) and "ใส่ใจ" (Care) are Teaching feature words. Given two sets of seed word from two categories as follow:

Teaching technique = {"lecture", "demonstration", "step", "structure", "emphasis", "collaborative"}

Personality = {"enthusiasm", "willing", "responsibility", "honor", "respect", "friendly}

Choose the three semantic similarity methods, e.g., Resnik method, Adapted Lesk-Tanimoto method, and Jiang and Conrath method. Then, compute their semantic similarity between the feature word and each seed words (as shown in Table 3.1).

Step 3) Counting the majority vote: Maximum numbers of similarity score of each categorize were counted. Following of above example, the "*Explain*" word, the Resnik method and Jiang & Conrath method provided maximum of similarity score with seed word of "*Teaching technique*" category. It has 2 out of 3 voter methods; therefore, the "*Explain*" word is assigned as member of "*Teaching technique*" category. While, "*Care*" word, is assigned into "*Personality*" category with 2 out of 3 voter methods.

Table 3.1 Demonstration of majority voting on semantic similarity

		Resnik				***Adapted Leak***				***Jiang & Conrath***			
Feature word	***"Explain"***	***n***	***v***	***a***	***r***	***n***	***v***	***a***	***r***	***n***	***v***	***a***	***r***
Teaching technique (C3)	*lecture*	-	***3.581***	-	-	-	0.132	-	-	-	***0.134***	-	-
	demonstration	-	-	-	-	-	-	-	-	-	-	-	-
	step	-	2.943	-	-	-	0.067	-	-	-	0.099	-	-
	structure	-	-	-	-	-	0.062	-	-	-	0.058	-	-
	emphasis	-	-	-	-	-	-	-	-	-	-	-	-
	collaborative	-	-	-	-	-	-	-	-	-	-	-	-
Personality (C6)	*enthusiasm*	-	-	-	-	-	-	-	-	-	-	-	-
	willing	-	-	-	-	-	-	-	-	-	-	-	-
	responsibility	-	-	-	-	-	-	-	-	-	-	-	-
	honor	-	-	-	-	-	0.119	-	-	-	0.073	-	-
	respect	-	-	-	-	-	***0.137***	-	-	-	0.074	-	-
	friendly	-	-	-	-	-	-	-	-	-	-	-	-
Feature word	***"Care"***	***n***	***v***	***a***	***r***	***n***	***v***	***a***	***r***	***n***	***v***	***a***	***r***
Teaching technique (C3)	*lecture*	3.383	-	-	-	0.066	0.087	-	-	0.085	0.070	-	-
	demonstration	3.383	-	-	-	0.088	-	-	-	***0.122***	-	-	-
	step	4.595	-	-	-	0.104	0.079	-	-	0.109	0.072	-	-
	structure	2.775	-	-	-	0.090	0.087	-	-	0.096	0.059	-	-
	emphasis	3.169	-	-	-	0.040	-	-	-	0.090	-	-	-
	collaborative	-	-	-	-	-	-	-	-	-	-	-	-

Table 3.1 Demonstration of majority voting on semantic similarity (continued)

Feature word	***"Care"***	***Resnik***				***Adapted Leak***				***Jiang & Conrath***			
		n	v	a	r	n	v	a	r	n	v	a	r
Personality (C6)	*enthusiasm*	***4.628***	-	-	-	0.178	-	-	-	0.120	-	-	-
	willing	4.100	-	-	-	0.146	-	-	-	0.076	-	-	-
	responsibility	-	-	-	-	***0.201***	-	-	-	0.106	-	-	-
	honor	3.169	3.132	-	-	0.049	0.145	-	-	0.097	0.098	-	-
	respect	***4.628***	3.132	-	-	0.180	0.136	-	-	0.087	0.100	-	-
	friendly	0.779	-	-	-	0.050	-	-	-	-	-	-	-

Scoring process

This framework used opinion score from SentiWordNet. The SentiWordNet is a linguistic resource which provides opinion score of word that related with WordNet synsets. Each word in SentiWordNet consists of two polarity score that are "*Positive*" and "*Negative*". There are several methods to use these scores (as described in Chapter 2). In this work, the average scores of opinion word that corresponded with their polarity can be computed as shown in following example:

Step 1) Identify polarity of opinion word: Suppose that a feedback sentence is "*อาจารย์อธิบายได้ชัดเจน*". This sentence was tokenized and Part-Of-Speech tagged as "*อาจารย์ (NCMN) / อธิบาย (VACT) / ได้ (XVAE) / ชัดเจน (ADVN)*". The word "*ชัดเจน*" was assigned as opinion word. Then, the polarity identification step predicts it's polarity to "*Positive*".

Step 2) Translated opinion word: The opinion word "*ชัดเจน*" is translated as "*Clearly*" using the LEXiTRON dictionary. The Part-Of-Speech "*ADVN*" was mapped as "*a*" in WordNet tagset. Text similarity method was mapped between "*Clearly*" of LEXiTRON to "*Clearly*" word of SentiWordNet.

Step 3) Retrieving opinion scores: from all synsets of the "*Clearly*" word from SentiWordNet (as shown in Figure 3.11). The arithmetic mean of opinion score is used to compute score of "*ชัดเจน*" as follows:

(0.250+0.125+0.000+0.375)/4 = 0.188 (of positive polarity)

Finally, the arithmetic mean of opinion score on each categorizes are used as input variables to estimate good teaching characteristics level. Indicating of good teaching characteristics level as explained in next section.

Figure 3.11 Opinion score from SentiWordNet

3. Aggregation and Visualization

As described in previous section, each good teaching characteristic category was separately computed their opinion score. This module aims to summarize all of those opinion score for indicating the quantitative levels of good teaching characteristics of individual teacher. This proposed module consists of two sub-modules are: 1) Good teaching characteristics aggregation and 2) Good teaching visualization.

3.1 Good teaching characteristics aggregation

This step aims to indicate level of good teaching of individual by aggregate all of opinion score for each category into a total good teaching score. The machine learning for regression is vital technique to estimate these good teaching level score as depicted in Figure 3.12.

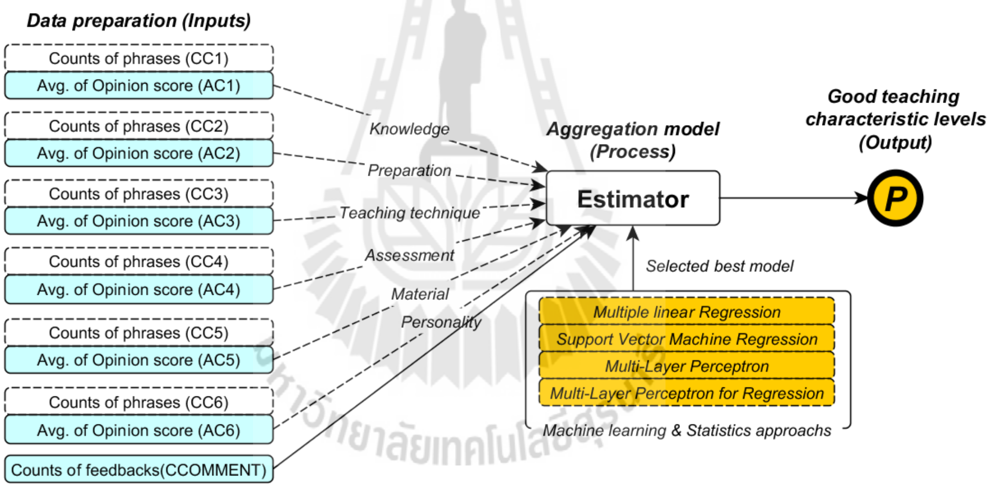


Figure 3.12 Estimation of good teaching characteristic level

The step of good teaching characteristics aggregation is as follows:

Step 1) Data preparation: in previous module, the feature word and their opinion score from student feedback are obtained. 13 variables of input data are used to train machine learning model. These variables consists of: 6 variables of the average of opinion score on each categories, 6 variables of total number of opinion words on each categorizes, and a variable of the total number of student feedbacks are used as input data. The output of the process is numerical value to indicate the level of good teaching.

Step 2) Aggregation model: the statistical and machine learning techniques are employed to model an aggregator. This aggregator used to summarize all input data as a numerical value of good teaching level. The WEKA is used as modeling application. Four well-known machine learning techniques are used as estimation model including:

- *Multiple Linear Regression (MLR)*: it is a statistical method which deals with several variables of input (x) to estimate one output (y). This model is similar to the simple linear regression that tries to map input and output on linear function. In WEKA, configurations of modeling environment are; 1) Using all variables of input data in regression function, 2) Eliminate co-linear attributes, and 3) Ridge parameter is 1.0-E8.

- *Support Vector Machine for Regression (SVR)*: it is an implement of the Support Vector Machine for regression task. With the characteristics of SVM, the optimal hyperplane of SVM can be considered as regression function. To model the SVR, parameters setting are: 1) The polynomial kernel $K(x,y) = < x, y >^p$ is used, where p is 1, and 2) The RegSMOImproved algorithm which proposed by Shevade *et al*., (2000) is selected as learning algorithm.

- *Multilayer Perceptron (MLP)*: it is a feed-forward of Artificial Neural Network. The learning algorithm of MLP is backpropagation process. In WEKA, classification task all of node in each layers (the hidden and output layer) used sigmoid function as activation functions. However, in case of estimation task (the output as numeric value) the unthreshold linear function is used as activation functions. The default parameter settings are: 1) the number of hidden layers is 1, 2) the number of nodes in hidden layer is 7. It is defaults number of nodes that can be computed by number of variables (variables + class) divided by 2, and 3) the learning rate and momentum are 0.3 and 0.2, respectively, and 4) All of numerical variables are normalized.

- *Multilayer Perceptron for Regression (MLPR)*: a variant type of MLP which proposed by Hall *et al.,* (2009). It consists of one hidden layer and optimization class by minimizing the squared error plus a quadratic penalty with the Broyden-Fletcher-Goldfarb-Shanno (BFGS) method. The ridge parameter is used to determine the penalty on the size of the weights estimation. The logistics function is used as activation function. Experimental configuration are; 1) the number of hidden units is 7 (this number based on MLP method as described above). 2) The ridge penalty factor is 0.01 (default), and 3) Instead of using BFGS method, the conjugate gradient descent method is used.

The model that delivered the highest performance would select as good teaching level estimator of this proposed framework.

Step 3) Knowledge storing: this is final step which all of extracted information about good teaching characteristics of individual teacher is stored in a database or specific purposed of knowledge base e.g., Good teaching characteristics ontology (Phiakoksong, Niwattanakul, and Angskun, 2013). The detail of good teaching characteristics data consisting of; 1) Detail of individual teachers (e.g. Teacher's name, Teacher's ID, etc.), 2) Student feedback paragraph, 3) The extracted feature word and their opinion, 4) The opinion score, 5) The average of opinion score of each categories of good teaching characteristics, and 6) The level of good teaching characteristics. The relation of these extracted information can depicted in Figure 3.13.

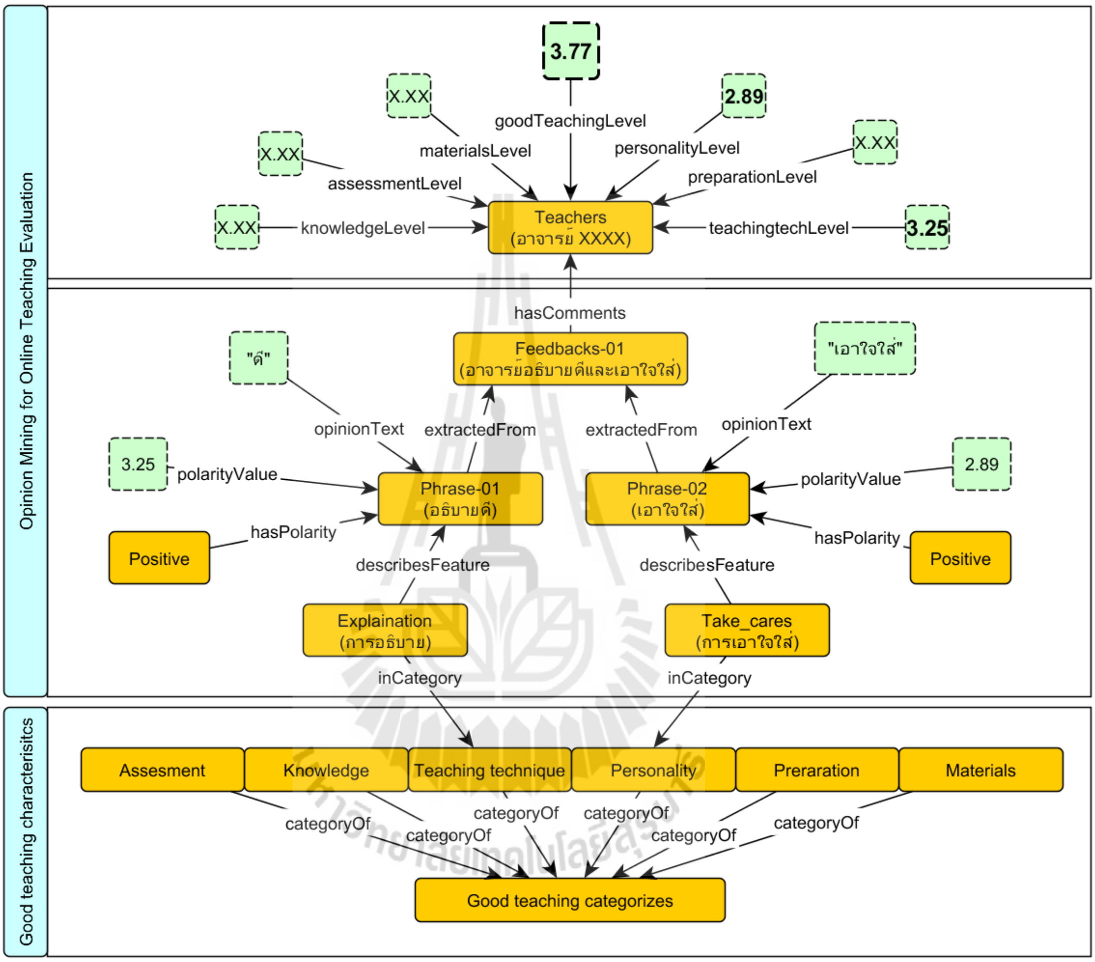


Figure 3.13 Represent of knowledge storing of an individual teacher

In this aggregation process, the estimator (machine learning model) is vital technique to obtain the good teaching characteristic level of each individual teacher. The model performance is measured and presented in Chapter 4.

3.2 Good teaching visualization

After, overall information was stored. A simple web interface was created. This interface is a simple way that provides benefit for all users includes educational administrators to monitor teaching quality of their faculty members. For instance, the useful knowledge can present via a website. This knowledge is retrieved from knowledge base and presented in subtle level correspond with educational institute administration process.

First of all, faculty level, overall scores and each categories score of good teaching characteristics are presented. A visualization tools called “Radar chart” (In practice, other types of visualization technique could also be used). This visualization provided benefit for users in the ease of perception about their faculty teaching performance. To consider in subtle level, list of hypertext anchors are prepared for link to each department as depicted in Figure 3.14.

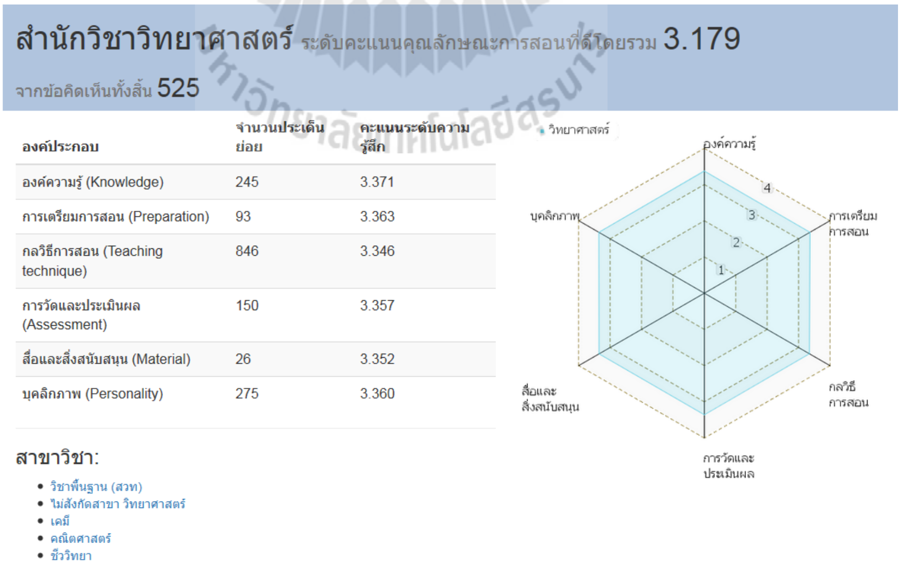


Figure 3.14 Good teaching characteristics in faculty level

Similarly to faculty level, table of score and radar chart was used to present score of department. Moreover, this level had shown list of department's members which is ranked by total score of good teaching characteristics. Arithmetic means on each good teaching characteristics component of individual instructors were presented. In additional, information popup window about sentiments polarity were prepared for user on each component. The number of positives, negatives, and neutrals polarity were shown as emoticon popup depend on each good teaching category as shown in Figure 3.15. Color shade is applied to indicate levels of teaching performance based on score on each teaching components.

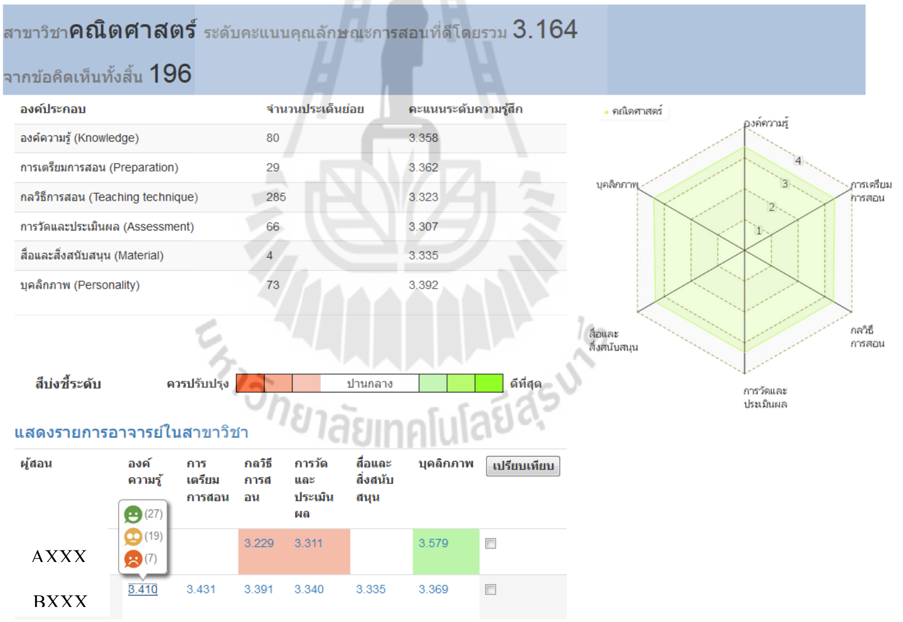


Figure 3.15 Good teaching characteristics in department level

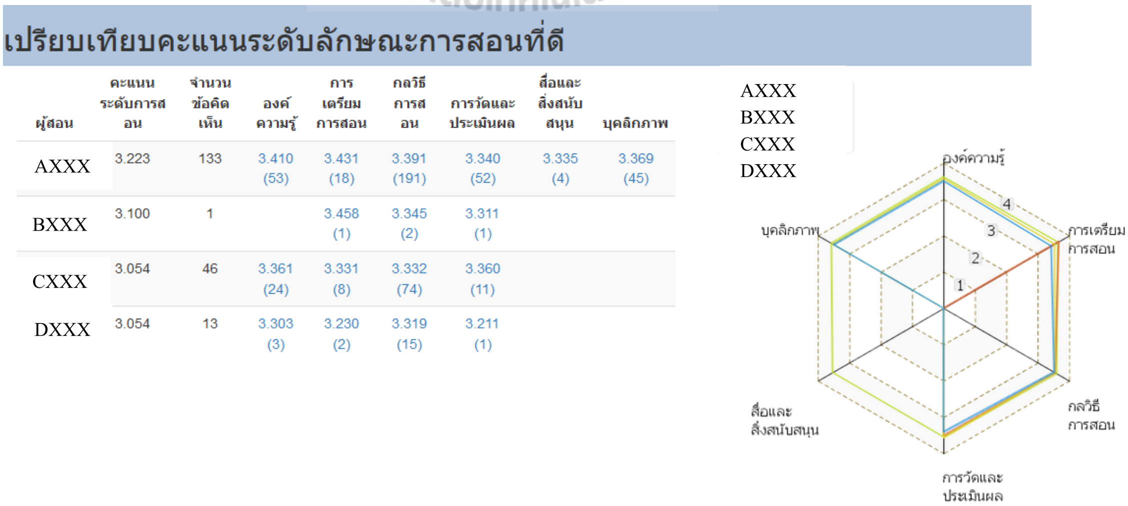
In individual level, basis of useful information are provided in same fashion with higher level. However, this level provided hypertext link to show detail of student comments belong to their component of good teaching characteristics.

The feature word and opinion word of each paragraph of student feedback were markup as color (as shown in Figure 3.16).

องค์ประกอบ	จำนวนประเด็นย่อย	คะแนนระดับความรู้สึก	รายละเอียด
องค์ความรู้ (Knowledge)	53	3.410	แสดงรายละเอียด
การเตรียมการสอน (Preparation)	18	3.431	แสดงรายละเอียด
กลวิธีการสอน (Teaching technique)	191	3.391	แสดงรายละเอียด
การวัดและประเมินผล (Assessment)	52	3.340	แสดงรายละเอียด
สื่อและสิ่งสนับสนุน (Material)	4	3.335	แสดงรายละเอียด
บุคลิกภาพ (Personality)	45	3.369	แสดงรายละเอียด

Figure 3.16 Good teaching characteristics in individual levels

For administration, these teaching performances could compare between individual teachers in their department which useful to indicate strength or weakness in teaching process of their faculty members as shown in Figure 3.17.



ผู้สอน	คะแนนระดับการสอน	จำนวนข้อคิดเห็น	องค์ความรู้	การเตรียมการสอน	กลวิธีการสอน	การวัดและประเมินผล	สื่อและสิ่งสนับสนุน	บุคลิกภาพ
AXXX	3.223	133	3.410 (53)	3.431 (18)	3.391 (191)	3.340 (52)	3.335 (4)	3.369 (45)
BXXX	3.100	1		3.458 (1)	3.345 (2)	3.311 (1)		
CXXX	3.054	46	3.361 (24)	3.331 (8)	3.332 (74)	3.360 (11)		
DXXX	3.054	13	3.303 (3)	3.230 (2)	3.319 (15)	3.211 (1)		

Figure 3.17 Comparison of Good teaching characteristics in individual levels

3.1.3 Evaluation of quality and performance of system

In previous section (Modeling and developing the framework), there are two important components that should be concerned. They are 1) the structure of good teaching characteristics, and 2) the performance of the proposed framework to analyze Thai student feedback. Evaluation of the quality and performance of this proposed framework are as follows:

1) The structure of good teaching characteristics

The good teaching characteristics model is studied based on several of good teaching characteristics that defined in previous work. Obtaining teaching characteristics that suitable with Thai educational context, social science research process is implemented. The items of good teaching characteristics from previous studies are summarized as questionnaire. The questionnaire is used in surveying the information from the Thai teachers and students in higher education level. The good teaching characteristics are modeled by utilizing the Structural Equation Modeling (SEM) technique. SEM is a set of statistical process that used to extract the latent concepts and find their relationships.

1.1) Evaluation of good teaching characteristics structure

To indicate whether the quality of obtained model is fitted with the empirical data. There are several statistical indicators were proposed. Hooper, Coughlan and Mullen (2008) were summarized these statistical indicators and their thresholds as shown in Table 3.2.

Table 3.2 Statistical indicators of SEM model fitting

Statistical indicators	Criteria values
Chi-square (χ^2)	Low χ^2 relative to degrees of freedom (df), where df=$\frac{1}{2}(n\times(n+1))-t$ with an insignificant *p*-value ($p > 0.05$)
Root Mean Square Error of Approximation (RMSEA)	Value less than 0.07
Goodness-of-fit index (GFI)	Value greater than 0.95
Adjusted goodness-of-fit index (AGFI)	Values greater than 0.95
Standardized root mean square residual (SRMR)	Value less than 0.08
Comparative fit index (CFI)	Value greater than 0.95

2) Performance of the prototype framework

Besides, the structure of good teaching characteristic that proposed in previous section. The performance of computational process in 1) The opinion analysis module and 2) Good teaching aggregation and summarization module are equally important. The sub-modules and overall performance were evaluated as follows:

2.1) Evaluation of sub-module performance

The three sub-modules consists of; 1) Feature/Opinion Extraction, 2) Polarity Identification, and 3) Good teaching characteristic aggregation. The first two sub-modules were evaluated with the common indicators including: Precision (P), Recall (R), f-measure (F) and Accuracy (A). The minimum threshold value of performance is at least 80% of accuracy score. The correctness of classification is represented as confusion matrix as shown in Table 3.3.

Table 3.3 Confusion matrix of classification

		Predicted class	
		Yes (+)	**No (-)**
Actual class	**Yes (+)**	*TP*	*FN*
	No (-)	*FP*	*TN*

Where, *TP (True positives)*: These are cases in which we predicted as Positive class, and they actually are the Positive class.

TN (true negatives): The cases were predicted as Negative class, and they are not in Negative class.

FP (false positives): The cases were predicted as Positive class, but they are not the Positive class (Also known as a “Type I error”).

FN (false negatives): The cases were predicted as Negative class, but they are the Positive class (Also known as a “Type II error”).

Using these terms, the performance of classification process can be evaluated as Equation 3.1-3.4.

$$Recall = \frac{TP}{(TP + FN)} \tag{3.1}$$

$$Precision = \frac{TP}{(TP + FP)} \tag{3.2}$$

$$Accuracy = \frac{TP + TN}{(TP + FP + FN + TN)} \tag{3.3}$$

$$F-measure = 2\times\frac{Precision\times Recall}{(Precision+Recall)} \quad (3.4)$$

In case of multi-classes classification, Macro-Averaged and Micro-Averaged are used to present their overall performance (Sokolova and Lapalme, 2009) as shown in Equation 3.5-3.6.

$$\left.\begin{aligned}
MacroAvg_r &= \frac{\sum_{i=1}^{N} Recall_i}{N}, \\
MacroAvg_p &= \frac{\sum_{i=1}^{N} Precision_i}{N}, \\
MacroAvg_a &= \frac{\sum_{i=1}^{N} Accuracy_i}{N} \\
MacroAvg_f &= \frac{\sum_{i=1}^{N} F-measure_i}{N}
\end{aligned}\right\} \quad (3.5)$$

$$\left.\begin{aligned}
MicroAvg_r &= \frac{\sum_{i=1}^{N} TP_i}{\sum_{i=1}^{N} (TP+FN)_i}, \\
MicroAvg_p &= \frac{\sum_{i=1}^{N} TP_i}{\sum_{i=1}^{N} (TP+FP)_i}, \\
MicroAvg_a &= \frac{\sum_{i=1}^{N} (TP+TN)_i}{\sum_{i=1}^{N} (TP+FP+FN+TN)_i} \\
MicroAvg_f &= 2\times\frac{MicroAvg_p\times MicroAvg_r}{(MicroAvg_p+MicroAvg_r)}
\end{aligned}\right\} \quad (3.6)$$

The last sub-module aim to estimate opinion scores and indicated the good teaching characteristic score that related with teaching evaluation score. The statistical indicators including: 1) the Mean Absolute Error (MAE) and 2) Root Mean Squared Error (RMSE) are used to compare performance of model. The MAE and RMSE are represented as Equation 3.7 and 3.8, respectively.

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|A_t - F_t\right| \tag{3.7}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(A_t - F_t\right)^2} \tag{3.8}$$

Where, A_t is actually score of teaching evaluation score of a teacher (t), F_t is estimated score of a teacher (t), and n is total number of teacher.

2.2) Evaluation of overall performance

The second objective of this work state that the expected performances of this propose framework has the high correlation with individual teaching evaluation score. To measure this correlation, the good teaching characteristics score from the proposed framework is measured against the total teaching evaluation score from close-end question. The Spearman's rho rank correlation (ρ) is used to indicate this performance. If X and Y are ranks, simplify the Pearson product-moment correlation coefficient (r) formula yields the following expressions as shown in Equation 3.9.

$$\rho = 1 - \frac{6\sum_{i=1}^{N} d_i^2}{N^3 - N} \tag{3.9}$$

Where, $d_i = X_i - Y_i$ is the difference in ranks of the two variables, and N is number of pairs between X and Y. The correlation coefficients always lie between -1 and +1. The more the correlation coefficient comes closer to -1 or +1. The sign symbol indicates the direction of correlation. The plus (+) sign shows that if X have higher ranking than the Y, it would have high ranks belong to X. The minus (-) sign is vice versa. The interpretations of spearman's rho rank correlation level are shown in Table 3.4.

Table 3.4 Strength of correlation value (Hinkle, Wiersma, and Jurs, 1998)

ρ	**Interpretation of correlation value**
0.90 - 1.00	Very strong
0.70 - 0.89	Strong
0.50 - 0.69	Moderate
0.30 - 0.49	Weak
0.00 - 0.29	Very weak

3.2 Population and samples

To identify good teaching characteristics that corresponds with Thai educational context. The population and samples for good teaching characteristic model is separated into two groups consisting of 1) Faculty: the full time instructors at Suranaree University of Technology (SUT), Thailand, and 2) Students: the learners who are studying at the undergraduate level at SUT. The table for determining sample size (Krejcie and Morgan, 1970) was used to determine sample size. The total amount of sample units consisting of 97 faculty and 474 students were selected with the simple random sampling technique.

3.3 Research Instruments

The instruments that utilized in this study divided into two groups including: 1) Design and development instruments and 2) Evaluation instruments.

3.3.1 Design and development instruments

In this section, two groups of instruments are presented.

1) Good teaching characteristics questionnaire: this questionnaire is construct based on summary from previous defined of good teaching characteristics. It consists of 66 question items with two types of answer that are:

1.1) Three choices answer: it comprises "*Yes, certainly (+1)*", "*Uncertain (0)*", "*Absolutely not (-1)*". This type of answer is used to identify items that are characteristics of good teaching, which appropriate with Thai educational context and

1.2) Rating scales (5 scales): this questionnaire is used to model the good teaching characteristics model for surveying data.

2) Instrument for design and develop the proposed system: selected applications and online services that have been utilized to develop the propose system is listed below:

- Java Development Kit 6 Update 20 or above
- LexTo: Thai Lexeme Tokenizer
- Apache OpenNLP version 1.4.3 (ORCHID tagset)
- SentiWordNet (Linguistics resources)

- WordNet (Lexical database of English)
- LEXiTRON, (Thai-English dictionary)
- WS4J: WordNet Similarity for Java
- WEKA 3.7.10 (Waikato Environment for Knowledge Analysis)

3.3.2 Instruments for Evaluation

Three instruments are used in evaluation process including:

1) LISREL: It is a windows application which consists of several statistical packages for analyzing and modeling data such as Structural Equation Modeling, Multilevel Structural Equation Modeling, Multilevel Linear and Nonlinear Modeling, Formal Inference-based Recursive Modeling and Generalized Linear Modeling. This study used the LISREL version 8.72 to analyze and model the good teaching characteristics.

2) Weka3 (Data Mining Software in Java): the Weka is a collection of machine learning algorithms for data mining tasks. The algorithms can either be applied directly to a dataset or called from Java code. Weka contains tools for data pre-processing, classification, regression, clustering, association rules, and visualization. It is also well-suited for developing new machine learning schemes (Hall *et al.*, 2009).

3) SPSS (Statistical Package for the Social Sciences): It was an integrated set of programs for the management and statistical analysis of social science data, developed especially for the processing and analysis of data from questionnaire surveys.

3.4 Data Collection and Analysis

There are two phases of data collecting and analyzing processes including:

1. Good teaching characteristics model: to analyze the good teaching characteristics, the steps of collecting data are as follows:

- The good teaching characteristic questionnaire are disseminate to the sample group (97 faculty and 474 students of Suranaree University of Technology).

- Given three weeks to collect the answered questionnaire from the sample group.

- Questionnaire's answer is encoded in appropriate format for LISREL application.

- Good teaching characteristics are modeled. The LISREL is used to fit model and the statistical indicators were computed. The important indicators that described in previous section (Section 3.1.3: Evaluation of quality and performance of system) are compared with the output statistical values to indicate the quality of model is fitted with the empirical data.

2. Performance of the proposed framework: the student's feedbacks are sampling from the Online Teaching Evaluation system of Suranaree University of Technology. These feedbacks are used in process of design and develop framework for mining student feedbacks. The performance of the three sub-modules consists of; (1) Feature/Opinion Extraction, (2) Polarity Identification, and (3) Good teaching characteristic aggregation, are measured via the WEKA and SPSS software.

According to the research methodology process as mentioned above, the experimental results and their performances are described in Chapter 4 and the conclusion and suggestion for future research are presented in Chapter 5.

CHAPTER 4

EXPERIMENTAL RESULTS AND DISCUSSIONS

This chapter presents the result of modeling and developing a framework to extract knowledge and useful information from online teaching evaluation. The first two sections will be presented the experimental result and their performance and last one is discussion section as follows:

4.1 The experiment and result of good teaching characteristics model

4.1.1 Evaluation of good teaching characteristics model

4.2 The experiment and result of the proposed framework

4.2.1 Evaluation of sub-module performance

4.2.2 Evaluation of overall performance

4.3 Discussions

4.3.1 The results of the hypothesis testing

4.3.2 The discussion of imperfect results

4.1 The experiment and result of good teaching characteristics model

Following the first objective of this study, that is “To identify the component of good teaching characteristics that corresponds with Thai educational context”. The social research process is implemented and their results are described in next section:

4.1.1 Evaluation of good teaching characteristics model

Experimental process*:*

1. The population is separated into two groups consisting of 1) Teachers: the full time instructors at Suranaree University of Technology (SUT), Thailand, and 2) Students: the learners who are studying at the undergraduate level at SUT. The table for determining sample size (Krejcie and Morgan, 1970) was used to determine sample size. The total amount of sample units consisting of 97 teachers and 474 students were selected with the simple random sampling technique.

2. Synthesizing the list of good teaching characteristics items from reviewing of literature as mentioned in section 2.1. The questionnaire which consists of 66 items based on the 6 teaching components were constructed (in Appendix I). The numbers of items of good teaching characteristics are roughly grouped as follows: *Knowledge* (4 items), *Preparation* (4 items), *Teaching technique* (28 items), *Assessment* (8 items), *Materials* (4 items), and *Personality* (18 items).

3. Testing the quality of questionnaire, The Index of Item Objective Congruence (IOC) and The Cronbach's α-coefficient (Cronbach, 1951) was computed. These question items are obtained IOC scores (for validity measurement) between 0.88 and 1.00, which above the minimum threshold (at 0.50). In aspect of reliability of questionnaire (based on Cronbach's α-coefficient), these questionnaires obtained a high reliability rate at 0.983.

Experimental results*:*

1. Identifying of good teaching characteristics items: The 66 items of closed-end questions with 3 choices of answers ("*Yes, certainly* (+1)", "*Uncertain* (0)", "*Absolutely not* (-1)") are answered by the samples. To indicate items that are

good teaching characteristics, the IOC score is adopted. The value of IOC at 0.50 is determined as a threshold. Any items of the questionnaire those are equal or higher than 0.5 are selected as good teaching characteristics. The IOC result is shown in Table 4.1.

Table 4.1 Identifying and selecting good teaching characteristics items

Initial Good teaching components	Number of selected items	IOC score			
		Teacher		Student	
		Min-Max	Average	Min-Max	Average
Knowledge	4	1.00-1.00	1.00	0.95-0.97	0.96
Preparation	4	0.98-1.00	0.99	0.97-0.98	0.97
Teaching	28	0.89-1.00	0.97	0.96-0.99	0.97
Assessment	8	0.96-1.00	0.98	0.95-0.97	0.97
Materials	4	0.83-1.00	0.94	0.97-0.98	0.98
Personality	18	0.94-1.00	0.98	0.97-0.98	0.98
Total	**66**	**0.83-1.00**	**0.98**	**0.95-0.99**	**0.97**

The results in Table 4.1 illustrated that the teachers and students indicated all of questionnaire items (66 items) describe the characteristics of good teaching. The teacher has given the IOC scores between 0.83 and 1.00. Teachers indicate that the knowledge (1.00) and preparation (0.99) are important factors of teaching characteristics. While the student indicated that the personality (0.98) and materials (0.98) are important factors of teaching characteristics in the aspects of students. These questionnaire items are used to develop a good teaching characteristics model.

2. Developing a good teaching characteristics model: Afterward, the 66 items with 5 point Likert scales questionnaire are answered. The Exploratory Factor

Analysis (EFA) and the second order Confirmatory Factor Analysis (second order CFA) are used to develop a good teaching characteristics model.

2.1) In the first stage, the EFA is employed to extract the principal factors (latent variables) and factor loading scores of each component. These principal factors are assigned as variables in the stages of model development. The factor loadings (the 1st factor loading) of these principal factors are obtained.

2.2) In the second stages, the second order CFA was used to model the good teaching characteristics from these principal factors. The factor loadings of the six core components are obtained (the 2nd factor loading). After that some conceptual key terms were redefined for covers the meaning of questionnaire items in each group as follows:

- "Knowledge" still used the original conceptual terminology. It describe about content and practical knowledge for teaching and answering the questions of students.

- "Teaching preparation" was used instead of "Preparation". It covers about preparation to teach (contents, process, and materials) before actual teaching.

- "Teaching techniques and strategies" was used instead of "Teaching technique" which covers about individual teaching technique and teaching plan (long term teaching plan) to transfer knowledge to their students, and also include ability to control his/her students in the classroom.

- "Measurement and evaluation" was used instead of "Assessment" which concern about ability to create testing question, individual teaching to judgment and validity of the evaluation process that provide the benefit to indicate achievements and learning progression of students.

- "Teaching media and materials" was used instead of "Material". It covers several kinds of resources that used to be learning resource. Moreover, it covers about creating and utilizing the suitable materials, and also covers about having teaching assistants to support his/her teaching process.

- "Personality" is still used the original conceptual terminology. It describes individual personal behavior of teacher and good human relations. This component affect to student attention in class and their relationship between teacher and their student.

The result of good teaching characteristics model and their statistical indicators are shown in Table 4.2.

Table 4.2 Core components and principal factors of good teaching characteristics model

Good teaching components	Principal factors of each components	Item No.	The 1st factor loading	The 2nd factor loading
1. Knowledge (*KNOWLEDG*)	1.1) Knowledge fundamental (*KN_FUND*)	1.1 – 1.4	0.280	2.55
2. Teaching preparation (*PREPARE*)	2.1) Teaching preparation (*TE_PREP*)	2.1 – 2.4	0.350	2.19

Table 4.2 Core components and principal factors of good teaching characteristics model (continued)

Good teaching components	Principal factors of each components	Item No.	The 1st factor loading	The 2nd factor loading
3. Teaching techniques and strategies (*TEACHNIQU*)	3.1) Knowledge transferring technique (*KN_TRANS*)	3.11 – 3.17	0.083	4.57
	3.2) Classroom administration (*CL_ADMIN*)	3.24 – 3.28	0.083	
	3.3) Utilizing the feedback (*UT_FEEDS*)	3.8 – 3.10	0.048	
	3.4) Practical knowledge transferring technique (*PT_KNOW*)	3.18 – 3.22	0.077	
	3.5) Supporting student-centered learning (*ST_CENT*)	3.4 – 3.7	0.056	
	3.6) Teaching is structured (*TE_STRUCT*)	3.1 – 3.3	0.090	
4. Measurement and evaluation (*ASSESSME*)	4.1) Measurement and evaluation Techniques (*ME_TECH*)	4.1 – 4.8	0.320	2.01
5. Teaching media and materials (*MATERIAL*)	5.1) Teaching material and personnel support (*TE_MATE*)	5.1 – 5.4	0.450	1.75
6. Personality (*PERSONAL*)	6.1) Human relationship (*HU_RELAT*)	6.6 – 6.18	0.160	3.90
	6.2) Individual personality (*INDI_PER*)	6.1 – 6.5	0.150	

χ^2 = *27.77, df=31, p-value = 0.63, RMSEA = 0.00, GFI= 0.99, AGFI= 0.98, CFI=1.00, SRMR = 0.019*

Table 4.2 showed that there are 12 factors (1^{st} factors) are explored in this questionnaire. Four out of the six components consist of one factor including: "Knowledge" (KN_FUND: 0.280), "Teaching preparation" (TE_PREP: 0.350), "Measurement and evaluation" (ME_TECH: 0.320) and "Teaching media and materials" (TE_MATE: 0.450) components. While "Teaching techniques and strategies" components consist of six factors with factor loading scores between 0.048 and 0.090 (UT_FEEDS: 0.048, ST_CENT: 0.056, PT_KNOW: 0.077, KN_TRANS: 0.083, CL_ADMIN: 0.083 and TE_STRUCT: 0.090). The "Personality" component consists of two factors with factor loading scores of 0.150 and 0.160 (INDI_PER: 0.150 and HU_RELAT: 0.160). The second order CFA revealed that the "Teaching techniques and strategies" component obtained the highest of the factor loading at 4.57. The next important component is the "Personality" component with the 3.90 of the factor loading.

To verify that this proposed model is fitted with the empirical data, the important statistical indicators are computed including: the Chi-Square is 27.77 where df = 31, *p*-value is 0.63, RMSEA is 0.00, GFI is 0.99, AGFI is 0.98, CFI is 1.00 and SRMR is 0.019. Compared with the threshold values (as mentioned in Chapter 3 Section 3.1.3), that is *p*-value > 0.05, RMSEA < 0.07, GFI > 0.95, AGFI > 0.95, CFI > 0.95 and SRMR < 0.08 (Hooper *et. al.*, 2008). These statistical indicators indicate that the good teaching characteristics model is consistent with the empirical data. The structure of this proposed model can be depicted in Figure 4.1.

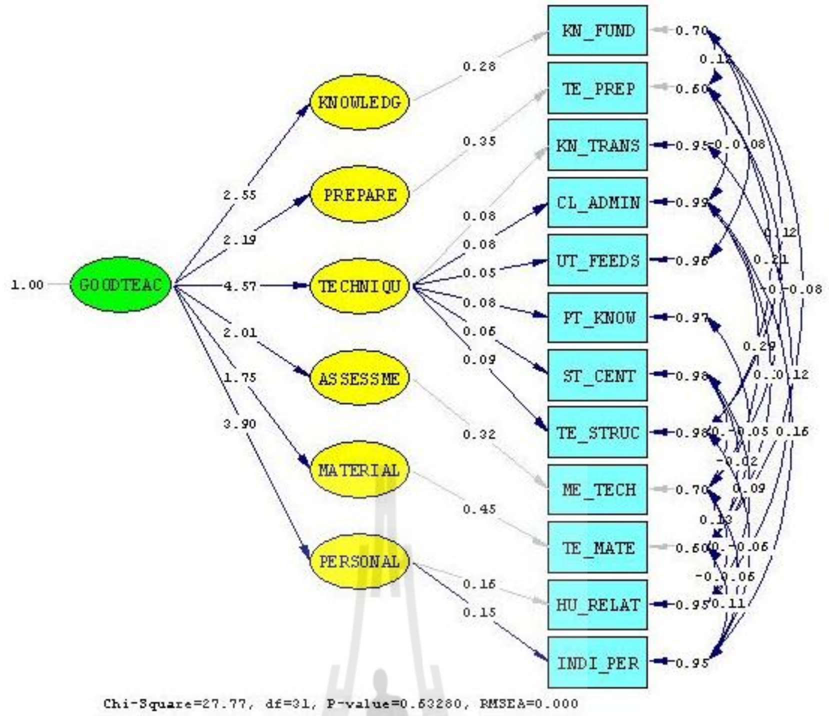


Figure 4.1 The structure of good teaching characteristics

4.2 The experiment and result of the proposed framework

Following the second objective of this study, that is "To design and develop an efficient opinion mining framework for analyze student feedback from online teaching evaluation corresponds to good teaching characteristics". An opinion mining process that deal with Thai student feedback was designed and developed. The machine learning and statistical technique are used as core process in several sub-modules. This section presents the performance of four sub-modules and overall performance of the proposed framework. The four sub-modules including: 1) Feature/Opinion extraction, 2) Polarity identification, 3) Opinion phrase scoring, and 4) Good teaching characteristic aggregation. While, overall performance is measured via level of rank correlation with the empirical data (i.e., teaching evaluation score from close-end question). The experimental results are as follows:

4.2.1 Evaluation of sub-module performance

1) Feature/Opinion extraction

This is a sub-module of "Opinion Analysis" module. The aims of this sub-module is extracted the feature and opinion word from student feedback paragraph. Their experimental process is as follow steps:

Experimental process*:*

The student feedbacks which are used in this experiment are obtained from Teaching Evaluation System of Suranaree University of Technology, Thailand. 500 of feedback paragraphs (a set of sentences) were randomly selected. The data were preprocessed via the Linguistic pre-processing module (Chapter 3: Figure 3.2). Then each paragraph was broken down into 3-gram data record. Finally, the 3,591 of 3-gram data records were obtained. The hold-out technique was applied to split both datasets into two parts. First part, 2,520 of data records were used as a training dataset to build the best two classifiers (the feature classifier and the opinion classifier). While 999 of remaining data records were reserved as validate dataset. Five Thai native speakers are asked to assign classes labels (eight categories of classes i.e. "*000*", "*001*", "*010*", "*100*", "*011*", "*110*", "*101*", and "*111*") for each 3-grams data record of both datasets. Two training datasets are obtained and used to model two effective classifiers. While the second dataset is used as test dataset to measure the performance of information extraction. This dataset consists of 1,351 words of vocabularies (478 of feature words, 396 of opinion words and 477 of undefined words).

Experimental results*:*

(1) Fragment classification: It is the first stage of this sub-module. The classifier is a vital technique of this stage. To construct two effective classifiers (Feature and Opinion classifiers), the four well known machine learning techniques are used in the experiment. They are 1) Naïve Bayes (NB), 2) Support Vector Machine (SVM), 3) K-nearest neighbor (KNN) with K=3, and 4) Classification Based on Associations (CBA) with parameter setting according to experimental of Hu and Liu (2006). These machine learning techniques modeled in WEKA environment on two training datasets (Feature dataset and Opinion datasets). The 10-fold cross-validation was used to measure the effectiveness of these classifiers. The best two classifiers were selected and used in the proposed framework. Their performance (Precision, Recall, F-measure and Accuracy) of these machines learning technique (as shown in Figure 4.2).

In Figure 4.2 indicates that the Support Vector Machine (SVM) seem to be the best classifier for all of word types. The SVM obtained 0.718 of precision (P), 0.726 of recall (R), 0.722 of f-measure (F), and 0.726 of accuracy (A) for classified *n*-gram feature data records. While classifying the opinion word, the SVM got 0.675 of precision, 0.689 of recall, 0.682 of f-measure, and 0.689 of accuracy.

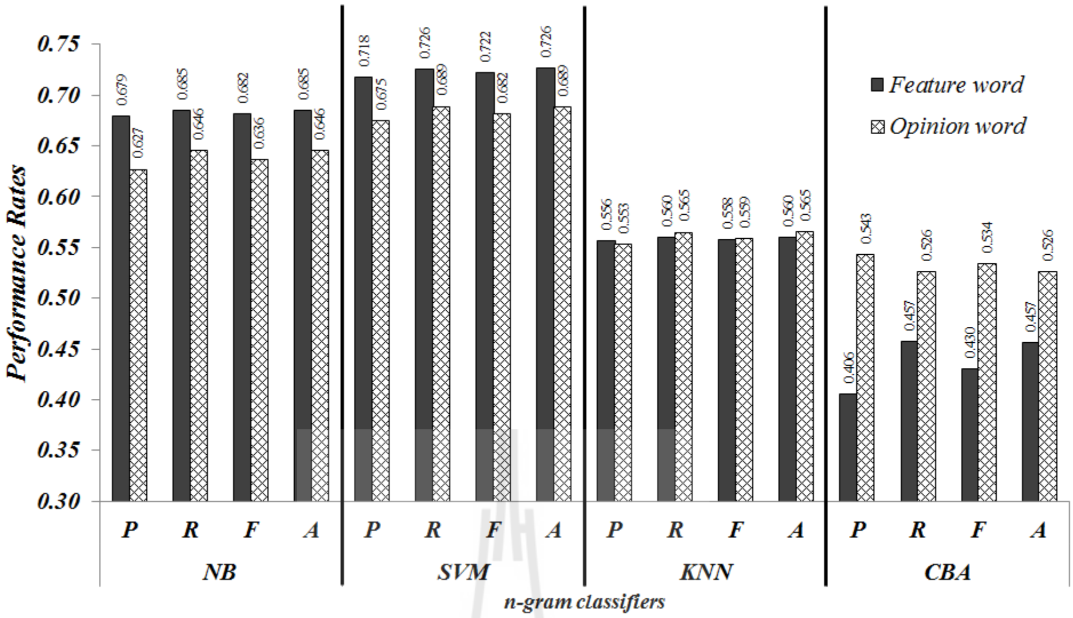


Figure 4.2 Performance measurement of feature and opinion classifier

Besides, the Naïve Bayes (NB) was a good candidate classifier. The NB got the performance more than 0.600 of every measure. Whereas the K-Nearest Neighbor (KNN) and Classification Based on Associations (CBA) classifiers got low performance (lower than 0.600 on overall evaluation). Because of this low performance result of the KNN and CBA classifiers, both of them were discarded to use in summarization step (Fragment summarization).

(2) Fragment summarization: It is the second stage which merges back each n-gram classification result original sentence to indicate which word is feature or opinion word. The *n*-gram majority voting was used with the best two classifier (Naïve Bayes and Support Vector Machine) results. The stop word was filtered with syntactic similarity are performed. The dataset consists of 1,351 words of vocabularies (478 of feature words, 396 of opinion words and 477 of undefined words). The confusion matrix and their performance are shown in Table 4.3 – 4.4.

Table 4.3 Confusion matrix of feature and opinion extraction

Naïve Bayes (NB)				***Support Vector Machine (SVM)***			
		Predicted				***Predicted***	
Feature word		***1***	***0***	***Feature word***		***1***	***0***
Actual	***1***	386	92	***Actual***	***1***	408	70
	0	60	813		***0***	106	767
		Predicted				***Predicted***	
Opinion word		***1***	***0***	***Opinion word***		***1***	***0***
Actual	***1***	271	125	***Actual***	***1***	264	132
	0	40	915		***0***	26	929

The results from Table 4.3 are used to compute the common evaluation values (e.g., Precision, Recall, F-measure and Accuracy) as shown in Table 4.4.

Table 4.4 Evaluation of extracting feature and opinion words

Classifier	***Type of word***	***P***	***R***	***F***	***A***
Naïve Bayes	***Feature***	**0.865**	**0.808**	**0.836**	**0.887**
	Opinion	0.871	0.684	0.766	0.878
Support Vector Machine	***Feature***	0.794	0.854	0.823	0.870
	Opinion	**0.910**	**0.667**	**0.770**	**0.883**

In Table 4.4, the evaluation results indicated that the Naïve Bayes (NB) classifier (with a fragment summarization process) was given the good performance for identifying feature words. All of evaluation (precision, recall, accuracy) were higher than 0.800. While the Support Vector Machine (SVM) classifier produced good performance for identifying opinion words. The precision was 0.910, recall is 0.667, f-measure is 0.770, and accuracy is 0.883.

2) Polarity Identification

The polarity words that obtained from previous sub-module was used as input data for the polarity identification module. The aim of this sub-module is to predict their polarity of given opinion word. Their experimental process can be described as follows;

Experimental process:

The opinion word that identified by previous sub-module were used. By expanding the word around this extracted opinion word in 3 window size. The 3-grams data records are obtained as follows. 500 feedback paragraphs of Thai students were randomly selected. They were break down into 2,519 of 3-grams data records. The classes of this n-grams dataset separated into three groups of polarity that are "*Positive*", "*Negative*", and "*Neutral*". The five Thai native speakers were asked to determine the appropriate class of these 3-grams data records. The polarity classes consist of 1,111 of Neutral, 930 of Positive, and 479 of Negative. Due to imbalance of Negative class, the Synthetic Minority Over-sampling Technique (SMOTE) technique was used to over-sampling the negative to 862 data records. The three well-known machine learning including; 1) Naïve Bayes (NB), 2) Support Vector Machine (SVM), 3) K-nearest neighbor (KNN) with K=3, and 4) Classification Based on Associations (CBA) were trained with this dataset. The best classifier is selected as polarity classifier of the proposed framework. The performances of three machine learning are described as follows:

Experimental results*:*

To measure the performances of these machine learning. The WEKA software with their default configuration is used to model. 1) K-nearest neighbor with (K=3), 2) Classification Based on Associations (CBA), 3) Naïve Bayes with default parameter and 4) Support Vector Machine with Linear Kernel. Their performances was tested with 10-folds cross validation. The confusion matrix and their performance can be illustrated in Table 4.5 – 4.6.

Table 4.5 Confusion matrix of polarity identification

K-nearest neighbor (KNN)		***Predicted***		
		Neutral	***Positive***	***Negative***
Actual	***Neutral***	845	134	132
	Positive	286	526	118
	Negative	166	135	561
Classification Based on Associations (CBA)		***Predicted***		
		Neutral	***Positive***	***Negative***
Actual	***Neutral***	802	166	143
	Positive	281	516	133
	Negative	264	265	333
Naïve Bayes (NB)		***Predicted***		
		Neutral	***Positive***	***Negative***
Actual	***Neutral***	871	140	100
	Positive	196	643	91
	Negative	98	79	685

Table 4.5 Confusion matrix of polarity identification (continued)

Support Vector Machine (SVM)		***Predicted***		
		Neutral	***Positive***	***Negative***
Actual	***Neutral***	978	88	45
	Positive	207	663	60
	Negative	94	71	697

The results from Table 4.5 are used to compute the common evaluation (precision, recall, f-measure and accuracy) as shown in Table 4.6.

Table 4.6 Evaluation of polarity identification

Classifier		***P***	***R***	***F***	***A***
K-nearest neighbor (KNN)	***Neutral***	0.651	0.760	0.701	0.752
	Positive	0.661	0.565	0.609	0.768
	Negative	0.691	0.650	0.670	0.810
	Micro-Avg	0.665	0.665	0.665	0.777
	Macro-Avg	0.668	0.658	0.663	0.777
Classification Based on Associations (CBA)	***Neutral***	0.595	0.721	0.652	0.705
	Positive	0.544	0.554	0.549	0.708
	Negative	0.546	0.386	0.452	0.722
	Micro-Avg	0.568	0.568	0.568	0.712
	Macro-Avg	0.562	0.554	0.558	0.712
Naïve Bayes (NB)	***Neutral***	0.748	0.784	0.766	0.816
	Positive	0.746	0.691	0.717	0.826
	Negative	0.782	0.795	0.788	0.873
	Micro-Avg	0.757	0.757	0.757	0.838
	Macro-Avg	0.759	0.757	0.758	0.838

Table 4.6 Evaluation of polarity identification (continued)

Classifier		***P***	***R***	***F***	***A***
Support Vector Machine (SVM)	***Neutral***	0.765	**0.880**	**0.818**	**0.850**
	Positive	**0.807**	0.713	0.757	**0.853**
	Negative	**0.869**	**0.809**	**0.838**	**0.907**
	Micro-Avg	**0.805**	**0.805**	**0.805**	**0.870**
	Macro-Avg	**0.813**	**0.801**	**0.807**	**0.870**

In Table 4.6, the evaluation results indicated that the Support Vector Machine (SVM) and Naïve Bayes (NB) classifiers produced the good performance for polarity identification. The accuracy of both classifier are higher than 0.80. However, consider the precision, recall and f-measure rate, the Support Vector Machine obtained the higher than 0.80 of the Micro and Macro-average of precision, recall, f-measure and accuracy, while other classifiers obtained the performance score less than 0.80.

3) Good teaching characteristic aggregation

The aim of this final sub-module is to indicate of the good teaching characteristics level of individual teacher. The result from previous sub-module (Opinion Phrase scoring) are used as input data. The output is numerical value which having range of score in 0.00 to 4.00 (correspond with teaching evaluation score). The high value of output indicates that the teacher has high characteristic of good teaching. On the other hand, the low value indicates that the teacher should improve their teaching. In aggregation process, the regression technique is main process. Several machine learning and statistical techniques are models and their performances are measured. Their experimental process of this sub-module is as follows:

Experimental process:

(1) 10,000 of student feedbacks are randomly selected to modeling an efficient aggregator. These feedbacks are processed follow the previous module of this proposed framework. The opinion scores are computed and used in the experiment.

(2) To model an estimator, the input data consisting of 13 variables. These variables consists of; the 6 variables of the average of opinion score on each categories, the 6 variables of total number of opinion phrases on each categories, and 1 variable of the total number of student feedbacks are used as input data. The output of this process is numerical value that used to indicate the level of good teaching characteristics.

(3) Four well-known machine learning techniques were used in experimental including; 1) Multiple Linear Regression (MLR), 2) Support Vector Machine for Regression (SVR), 3) Multi-layer Perceptron (MLP) and 4) Multi-layer Perceptron for Regression (MLPR). The 10-folds cross-validation is used as testing mode.

The performance of these four machine learning and statistical technique are described as follows:

Experimental results:

The four machines learning against with opinion scores are summarized as shown in Table 4.7.

Table 4.7 Performance of good teaching characteristic estimator

Input score (opinion score)	***Models***	***MAE***	***RMSE***
SentiWordNet	***MLR***	0.1694	0.2257
	MLP	0.1995	0.2689
	MLPR	0.1822	0.2449
	SVR	0.1696	0.2271

As shown in Table 4.7, all models are obtained the MAE and RMSE rate less than 0.30. The Multiple Linear Regression (MLR) and the Support Vector Machine for Regression (SVR) delivered the best estimation score. The MAE and RMSE rate of SVR are lower than other models.

4.2.2 Evaluation of overall performance

As described in previous section, all of sub-modules are important component of the proposed framework. The final results of this proposed framework indicate the good teaching characteristics of individual teacher. Normally, the total teaching evaluation score from close-ended question imply how much the student prefers in their teacher. Evaluating overall performance, the correlation coefficient of ranking between the rank of total teaching evaluation score and ranking from aggregation opinion score module should be in high level. The experimental process of the proposed framework is as follows:

Experimental process:

(1) 40,000 of student feedback are randomly selected. These feedbacks were processed follow the proposed framework as described above. The data distribution of these feedbacks can be depicted in Figure 4.3.

(2) These student feedbacks were drawn from 585 teachers; the median of these feedbacks is 23 feedbacks per a teacher. The minimum number of feedback is 1 and maximum is 1,327. The range value is 1,326 feedbacks. It has the right skewness characteristic. According to this characteristic, these feedbacks data were separated into 5 groups follow the percentiles of data. These groups consist of; 1) 1-4 feedbacks (20 percentiles), 2) 5-14 feedbacks (40 percentiles), 3) 15-38 feedbacks (60 percentiles), 4) 39-106 feedbacks (80 percentiles), and 5) More than 106 feedback (100 percentiles).

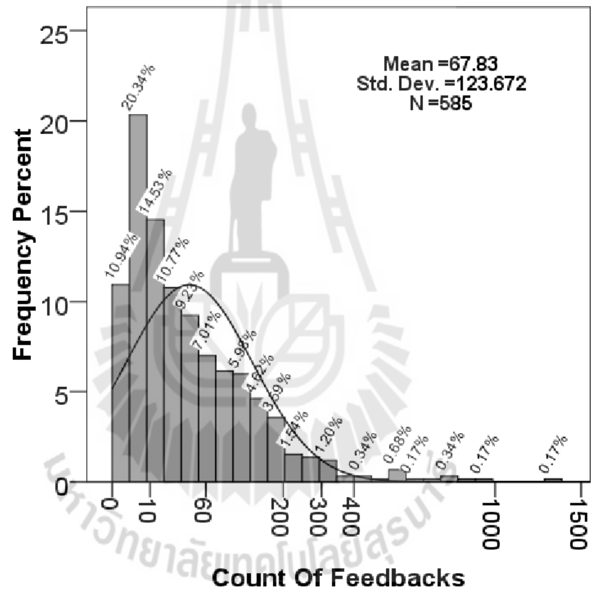


Figure 4.3 The distribution of student's feedback data

As described in previous section, the overall performance of the proposed framework as follows:

Experimental results:

The expectation of this study is that the proposed framework had the correctness of ranking at high level (greater than or equal 70% of ranking correlation). The statistical indicator called "*Spearman-rho rank order correlation*" is used to measure this performance. The ranking correlation is computed between the ranks of good teaching characteristics of proposed framework against with the rank from teaching evaluation score. Interpretation of the correlation values follows the criteria in Table 3.4 (Chapter 3). The criteria levels are 0.70-0.89 is strong correlation, and 0.50-0.69 is moderate. The spearman-rho rank order correlation is shown in Table 4.8.

Table 4.8 Spearman's rho rank order correlation of overall performance

Aggregation method	***N***	***Correlation Coefficient***	***p-value***
Average of SWN	585	0.132	1.412E-03**
MLR	585	0.273	1.977E-11**
SVR	585	0.294	3.632E-13**
MLP	585	0.543	4.121E-46**
MLPR	585	***0.689***	***1.395E-83***

** *p-value* $\leq$ 0.01 (*N* > 30, use the critical value from Pearson's correlation)

As shown in Table 4.8, using the Multi-Layer Perceptron for Regression provided moderate performance (more than 0.689). While, directly used of average of SentiWordNet score provided the lowest of rank correlation at 0.132.

Considering on number of feedback distribution, the performance of Multi-Layer Perception for Regression (MLPR) evaluated with the group of feedbacks (as depicted in Figure 4.4). The result indicated that group that had student feedbacks more than 107 delivered a high level of rank correlation at 0.777. When cumulated with the group that had student feedbacks more than 39. The rank correlation decreased to 0.722. Totally, the overall ranking correlation of MLPR is r = 0.689 which closely to strong level of rank correlation.

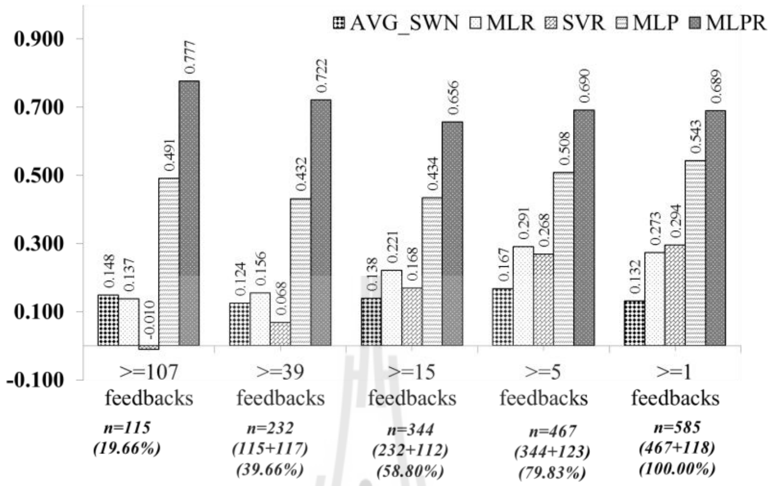


Figure 4.4 Spearman-rho rank correlation coefficient on cumulative of five groups

As described above, the Multi-Layer Perception for Regression (MLPR) gave good performance to indicate quality of teaching. The final model of MLPR can be depicted as Figure 4.5

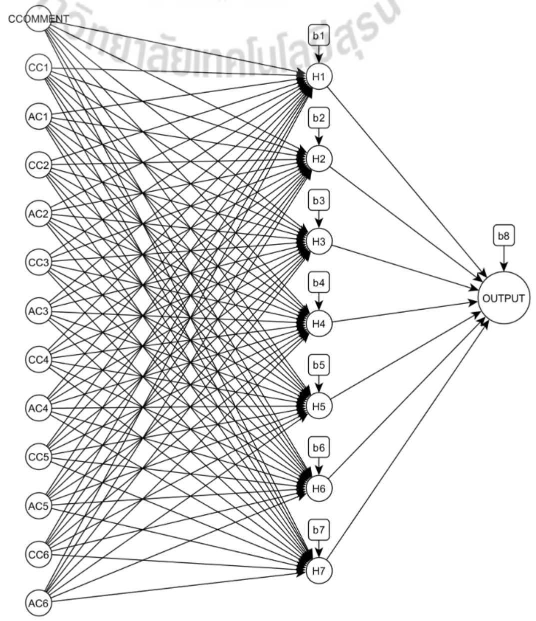


Figure 4.5 The multi-layer perception for regression model

the optimal weight parameter of this model is shown in Table 4.9.

Table 4.9 The optimal weight parameter of MLPR model

Input node	***Weight of node (Input → Hidden)***	***Weight of node (Hidden → Output)***
	H1	-4.496
CCOMMENT	-0.479	
CC1	-1.334	
AC1	-1.426	
CC2	0.646	
AC2	0.063	
CC3	-5.850	
AC3	0.817	
CC4	1.634	
AC4	-0.426	
CC5	0.619	
AC5	-0.173	
CC6	-4.366	
AC6	-1.967	
Bias (b1)	-1.978	
	H2	-4.971
CCOMMENT	-0.187	
CC1	1.306	
AC1	1.044	
CC2	1.076	
AC2	-0.378	
CC3	5.748	
AC3	-0.452	
CC4	-1.814	
AC4	0.093	
CC5	0.273	
AC5	0.289	
CC6	3.410	
AC6	1.306	
Bias (b2)	2.344	
	H3	1.249
CCOMMENT	3.020	
CC1	-5.669	
AC1	3.907	
CC2	-4.201	
AC2	1.373	
CC3	2.833	

Table 4.9 The optimal weight parameter of MLPR model (continued)

Input node	*Weight of node (Input → Hidden)*	*Weight of node (Hidden → Output)*
AC3	0.755	
CC4	0.303	
AC4	-1.444	
CC5	-1.250	
AC5	1.760	
CC6	1.950	
AC6	-1.319	
Bias (b3)	-1.473	
	H4	4.363
CCOMMENT	1.138	
CC1	1.315	
AC1	0.240	
CC2	-0.248	
AC2	0.218	
CC3	-0.595	
AC3	0.718	
CC4	-0.479	
AC4	0.080	
CC5	-0.128	
AC5	0.332	
CC6	-0.895	
AC6	0.078	
Bias (b4)	2.201	
	H5	-1.426
CCOMMENT	-6.047	
CC1	-0.450	
AC1	1.383	
CC2	5.698	
AC2	2.931	
CC3	-5.771	
AC3	1.053	
CC4	2.967	
AC4	1.631	
CC5	1.157	
AC5	1.108	
CC6	-6.930	
AC6	-0.471	
Bias (b5)	-2.124	

Table 4.9 The optimal weight parameter of MLPR model (continued)

Input node	***Weight of node (Input → Hidden)***	***Weight of node (Hidden → Output)***
	H6	-2.228
CCOMMENT	3.502	
CC1	-0.757	
AC1	0.481	
CC2	-4.580	
AC2	0.389	
CC3	0.517	
AC3	-0.759	
CC4	-0.410	
AC4	-1.219	
CC5	-0.084	
AC5	1.773	
CC6	1.609	
AC6	-0.600	
Bias (b6)	-1.785	
	H7	1.640
CCOMMENT	-5.826	
CC1	-0.877	
AC1	-0.594	
CC2	2.175	
AC2	-0.182	
CC3	5.248	
AC3	-0.926	
CC4	-0.354	
AC4	-0.661	
CC5	4.116	
AC5	1.460	
CC6	2.513	
AC6	-0.281	
Bias (b7)	2.749	
Bias of output (b8)		0.861

4.3 Discussions

As mentioned in the Chapter 1, the main purposes of this study are; 1) To identify the component of good teaching characteristics that corresponds with Thai educational context, and 2) To design and develop an efficient opinion mining framework for analyze student feedback from online teaching evaluation corresponds to good teaching characteristics.

4.3.1 The results of the hypothesis testing

The two main hypothesis of this research are 1) Obtain the extract component of good teaching characteristics which correspond with Thai educational context, and 2) Obtain an efficient opinion mining framework to indicate the strength and weakness of individual teaching from Thai student feedback, correctly with ranking correlation at high level (greater than or equal 70% of ranking correlation).

The First Research Hypothesis:

The evaluation results of modeling good teaching characteristics (Section 4.1) showed that the good teaching characteristics base on educational theory consist of 6 components including:

1. Knowledge

    1.1 Knowledge fundamental

2. Teaching preparation

    2.1 Teaching preparation

3. Teaching techniques and strategies

    3.1 Knowledge transferring technique

    3.2 Classroom administration

3.3 Utilizing the feedback

3.4 Practical knowledge transferring technique

3.5 Supporting student-centered learning

3.6 Structured teaching

4. Measurement and evaluation

4.1 Measurement and evaluation Techniques

5. Teaching media and materials

5.1 Teaching material and personnel support

6. Personality

6.1 Human relationship

6.2 Individual personality

The important component of good teaching characteristics are "Teaching technique", "Personality", "Knowledge", "Preparation", "Assessment", and "Material", respectively. The statistical indicators of this good teaching characteristic model are χ^2 = 27.77 (p-value = 0.63) where df = 31, $RMSEA$ = 0.00, GFI = 0.99, $AGFI$ = 0.98, CFI = 1.00, and $SRMR$ = 0.019. These statistical indicators indicated that the proposed of good teaching characteristic model is correspond with the educational context of teacher and student of SUT.

The Second Research Hypothesis:

Obtaining an efficient opinion mining framework to indicate the strength and weakness of individual teaching from Thai student feedback, correctly with ranking correlation at high level (greater than or equal 70% of ranking correlation).

As described in Section 4.2, the results of sub-modules and overall performance are reported. Most of sub-modules relied on the machine learning technique. The efficient of sub-module consist of; 1) *Feature/Opinion extraction* has the higher rate of accuracy (0.887) for feature word extraction with Naïve Bayes, and the accuracy at 0.883 for opinion word extraction with Support Vector Machine, 2) *Polarity identification* has the higher rate of accuracy (0.870) by using Support Vector Machine, and 3) *Good teaching characteristic aggregation* have the MAE and RMSE rate less than 0.30 for all machine learning model.

The overall performance of the proposed framework was measured by the Spearman-rho rank correlation. The statistical results shown that the Multi-Layer Perceptron for Regression (MLPR) yields the high level of rank correlation (r=0.689) with statistical significant at 0.01. Considering with cumulative of sub-groups, the Multi-Layer Perceptron for Regression (MLPR) yields the highest level of correlation at 0.777 in the group that has feedback more than 107 feedbacks. However, there is decreasing of the correlation rate when cumulated with other groups that have the low number of student feedbacks.

4.3.2 The discussion of imperfect results

Although, the evaluation results of sub-modules and overall performance of the proposed framework are high performance. However, there are imperfect occurred in these evaluation results. Many reasons for the imperfect results of these sub-modules are discussed as follows:

1) The effect of un-coverage and small size of training dataset, at initial stage of opinion mining, the feature and their opinion word extraction. Generally, previous studies used the dependency syntactic rule as extraction tool.

It provided good performance for many languages which have strictly grammatical pattern. However, Thai language is flexible syntactic grammar which can re-arrange word position. Moreover, Thai language does not use the punctuation or blank space to break a sentence. This characteristic make Thai language has the complicated structure. This study proposed a process which used machine learning technique as extraction process. The prerequisite of machine learning required the large enough and coverage of linguistic data in the interesting domain. Using the small size of training dataset affects to efficiency of the classifier.

2) The lacking of terminology in the educational context. This study used terminology from the LEXiTRON dictionary which is the general purposed dictionary. However, terminologies in educational context is specific terminology such as special word, abbreviated, slang word, etc. These words usually occurred during analysis process. To obtain better performance, these words need to be classified and organized by the knowledge experts in educational domain. Example of these words are "ห้องปฏิบัติการ", "ห้องแล็บ", "ห้องทดลอง", "Laboratory", "LAB", etc. should be categorized into a concept word.

3) The lacking of Thai subjective lexicon development. Several linguistic subjective lexicons are available e.g., SentiWordNet, WordNet-Affect, SenticNet, MPQA Opinion Corpus, etc. However, most of previous work that dealt with Thai language usually developed their own subjective linguistic lexicon. There is no evidence that formal lexicon of Thai subjective lexicon was deployed. Because of this reason, this study used the translation process to link between Thai and English language. This translation process affect to performance of many tasks in the proposed

framework. Moreover, the subjective score (opinion score) that develop from the different language may not suitable to directly apply with another context.

The last but not the least, the overall of this study is summarized and some recommendations for future research are presented in Chapter 5.

CHAPTER 5

CONCLUSIONS AND RESEARCH RECOMMENDATIONS

This chapter presents a summary of the research findings, the limitation of this study and recommendations for future research studies.

5.1 Summary of the research findings

This study aims to identify the good teaching characteristics and develop an efficient opinion mining framework for extract knowledge from student feedbacks. To identify the good teaching characteristics, the social research process is implemented. Reviewing of previous educational researches that related with characteristics of good teaching is summarized. The Likert scale questionnaire about good teaching characteristic is developed for data surveying. This questionnaire consists of 66 items based on the characteristic of good teaching from previous studies. The population and sample units draw from the full time instructors and students of Suranaree University of Technology. The total amount of sample units consists of 97 faculty and 474 students. The reliability of this questionnaire is in high level at 0.983. The indexes of item objective congruence (IOC) of each item are higher than the threshold value at 0.50. The Structural Equation Modeling (SEM) approach is used to model the structure of good teaching characteristics. The Exploratory Factor Analysis (CFA) and the secondary order Confirmative Factor Analysis between the observed variables and the latent variables are computed. The SEM statistical indicators indicated that the good teaching characteristics model correspond with the empirical data that survey from teachers and students in Thai educational context.

Finally, the opinion mining framework for extracting knowledge from student feedbacks is designed and developed. This framework consist of three main model including; 1) Linguistic pre-processing, 2) Opinion analysis, and 3) Aggregation and Visualization. The first main module is data pre-preparation process that separate text paragraph to word and tag their Part-Of-Speech. The second main module consists of three sub-modules including; 1) Feature/Opinion extraction, 2) Polarity identification, and 3) Opinion phrase scoring. These sub-modules are mined the subjectivity from student feedbacks. These subjective indicate which characteristics in teaching process are satisfied. In Feature/Opinion extraction, Naïve Bayes classifier and Support Vector Machine with *n*-gram majority voting are used as Feature and Opinion word extractors, respectively. In Polarity identification sub-module, Support Vector Machine is used as polarity identification from the given opinion word. The last sub-module of opinion analysis is Opinion scoring. The feature words are categorized by using majority voting based on semantic similarity score. While the score of opinion words are obtained from SentiWordNet. Finally, the third main module consists of only two sub-modules. First sub-module is Good teaching aggregation. This sub module aims to aggregate the score of six good teaching characteristics as a numerical value (total score). This numerical value used to as indicator of individual good teaching characteristics level. The Multi-Layer Perceptron for Regression model is the best estimator for indicate good teaching characteristics level. Finally, Good teaching visualization is used to visualizing all information including; teacher detail, student feedback, feature and opinion word, their score, and good teaching characteristics level for aggregation. These information are stored in a database for later retrieve, reuse and visualization in subtle levels.

The research findings are summarized as follows:

5.1.1 Identifying the good teaching characteristics, the questionnaire about good teaching characteristics is developed based on the previous studies. 97 teachers and 474 students of Suranaree University of Technology are answered these questionnaire. The SEM approach is used to model the good teaching characteristics. The good teaching characteristics consist of six components including; 1) Knowledge, 2) Teaching preparation, 3) Teaching techniques and strategies, 4) Measurement and evaluation, 5) Teaching media and materials and, 6) Personality. The good teaching characteristic model consists of 12 observed variables (*n*) which summarized from 66 items of questionnaire. 47 parameters (*t*) of paths and covariance coefficients of model have to estimate. The statistical indicator results of SEM are $\chi^2 = 27.77$ (p-value = 0.63) where $df = 31$, $RMSEA = 0.00$, $GFI = 0.99$, $AGFI = 0.98$, $CFI = 1.00$, $SRMR = 0.019$. Compared with the threshold values that is p-value > 0.05, $RMSEA < 0.07$, $GFI > 0.95$, $AGFI > 0.95$, $CFI > 0.95$ and $SRMR < 0.08$. These statistical indicators result passed the standard threshold. These comparisons indicate that the good teaching characteristics model consistent with the empirical data from teachers and students.

5.1.2 To develop an efficient opinion mining framework for indicating the strength and weakness of individual teaching from Thai student feedback. The efficient framework consists of; 1) Feature/Opinion extraction sub-module: the Naïve Bayes model delivered high rates of performances to extract feature words (the precision at 0.865, recall at 0.808, accuracy at 0.887, and f-measure at 0.836).

While the Support Vector Machine model delivered high rates of performances to extract opinion words (the precision at 0.910, recall at 0.667, accuracy at 0.883, and f-measure at 0.770). 2) Polarity identification sub-module have the high rate of performances (precision at 0.813, recall at 0.801, accuracy at 0.870, and f-measure at 0.807) by using the Support Vector Machine, and 3) Good teaching characteristic aggregation sub-module, the four well known of machine learning models consisting of Multiple Linear Regression (MLR), Support Vector Machine for Regression (SVR), Multi-Layer Perceptron (MLP), and Multi-Layer Perceptron for Regression (MLPR) given the MAE and RMSE rates less than 0.30 for good teaching score estimation. The overall performance of the proposed framework is measured by the Spearman-rho rank order correlation. The statistical results shown that the Multi-Layer Perceptron for Regression is the best model that delivered the high level of rank correlation ($r = 0.689$) with statistical significant at 0.01. Considering in the number of feedbacks per each teacher, the group which have feedback more than 107 per teacher obtained high level of ranking correlation ($r = 0.777$). Cumulative with the other groups (≥ 39 feedbacks, ≥ 15 feedbacks, ≥ 5 feedbacks, and ≥ 1 feedback), they obtained the ranking correlation equal to 0.722, 0.656, 0.690 and 0.689 with statistical significant at 0.01, respectively.

5.2 The limitation of the study

The limitation of the design and development of an efficient opinion mining framework for extracting knowledge from student feedbacks are described as follows:

5.2.1 This research deals with Thai natural language by analyzing unstructured texts that stored in an online teaching evaluation system. Due to a natural language is typically used for human communication, the language usage based on individual expression which is arbitrary distinction. Generally, most of the previous work deals with English language which used the dependency syntactic rule to extract information. The dependency syntactic rules deliver the good performance with the language that has strictly grammatical structure. However, there is no strictly grammatical structure in Thai language. Thai language also does not used punctuation to break a sentence. Therefore, this study used the machine learning technique instead of dependency syntactic rule. Although the machine learning deliver good performance in many research, however, the large enough and coverage of the sample cases of training dataset is required. Small size and un-coverage of training dataset yield unable to extract all of the feature and opinion words, which affected to consequences stage of the proposed framework.

5.2.2 Lacking of Thai subjective lexicon for directly used. The word translation process by Thai–English dictionary is used as background technique. Then, these words are mapped to terminology in SentiWordNet. Unfortunately, un-coverage between Thai and English vocabulary affected many words could not be translated. Consequently of incomplete of translation affect many feature word and opinion word cannot assign their scores. Moreover, many emerging words or phrases including idioms, proverbs, slangs, and transliteration word, are often written in student feedback. These words affected the proposed framework does not automatically categorize those words into the proper predefined categories; although, there are attempt to use semantic similarity approach. However, it still relies on the word translation process.

5.3 The application of the study

The benefit of this research could be useful in educational administration. In individual level, the teacher perceives their strength and weakness of teaching and learning process. This knowledge can be used to improve their teaching style in current semester, and also use as fundamental knowledge to design the teaching and learning activity for the next semester.

In administration, the information from student feedback can be used to indicate the teaching performance of faculty members. The administrator can consider this useful information and assign the training course for the teacher who has some weakness in teaching, promoting the teacher who obtained the good teaching characteristics, or to design the group of teaching expertise to be mentors for new faculty members.

In collaboration between institutes, if there is disclosure information, it possible to exchange the teachers between institutions which provide benefit for improving quality of education.

In addition, the design of this proposed framework could be applied to analyze other type of Thai text paragraph, such as column news, essay answers, or other reviews (e.g. product and service reviews, book reviews, etc.)

5.4 Recommendation for future study

There are some improvements that could be performed in the near future as described below:

5.4.1 Developing the educational terminology lexicon is necessary for feature and opinion word extraction. Every type of words (e.g., slang, abbreviate, transliteration word, etc.) should categorize into a concept word and store in a well-structure such as taxonomy or ontology. It could provide good benefit for decreasing the operation time and deliver higher accuracy of results.

5.4.2 Developing Thai opinion word lexicon, the opinion lexicon which was developed in different language and different context affect to the opinion score determination. To obtain the better performance, developing Thai opinion word lexicon with their score similar to SentiWordNet, is a solution to deliver higher performance of opinion score aggregation.

5.4.3 Thai language has delicate level of subjective expression which different from other languages e.g. "ดีมาก", "ดีเยี่ยม", "ดีที่สุด", "เจ๋ง", "แจ่ม", "แจ๋ว", etc. Implementing of syntactic rule to extract modifier of the opinion score, and estimate their score in subtle level with the sophisticate technique (e.g. Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), HIT algorithm, etc.) would provide the fine-gain score for indicating the good teaching characteristics of individual teacher.

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APPENDIX A

Good Teaching Characteristics

Questionnaire Items

GOOD TEACHING CHARACTERISTICS

QUESTIONNAIRE ITEMS

List of Good teaching characteristics	Yes, certainly					Uncertain	Absolutely not
	5	**4**	**3**	**2**	**1**		
1. ความรู้ความชำนาญ (Knowledge)							
1.1 มีความรู้ความเข้าใจที่เพียงพอต่อการตอบข้อคำถามของผู้เรียนส่วนใหญ่ (Having sufficient knowledge to answer the most of question from student.)							
1.2 มีความรู้เพียงพอที่ช่วยและส่งเสริมให้ผู้เรียนรู้และเข้าใจในหลักการของรายวิชาได้ (Having sufficient knowledge for help and support the learner to understand in principle of subject.)							
1.3 มีความรู้ที่จะช่วยแนะนำผู้เรียนในการค้นคว้า หาข้อมูลสารสนเทศที่ ถูกต้อง เหมาะสม (Having of knowledge to suggest the student to research and finding the relevant information.)							
1.4 รักษา/เพิ่มพูนคุณภาพทางวิชาการ โดยการศึกษา ค้นคว้า เข้าร่วมกิจกรรมหรือทำงานร่วมกับผู้อื่นในแวดวงวิชาการ (Retain and increase own academic knowledge from research and participate with colleague.)							
2. การเตรียมการสอน (Preparation)							
2.1 มีวัตถุประสงค์การเรียนรู้ที่เหมาะสม ชัดเจน (Having the suitable and clarify of objective learning.)							
2.2 มีโครงสร้าง เนื้อหาเป็นลำดับ มีความต่อเนื่อง (Having the structural and sequence of contents.)							
2.3 มีการจัดเตรียมเอกสารและแหล่งข้อมูลอ้างอิงต่าง ๆ ไว้เป็นอย่างดี (Having to prepare documents and information resource.)							
2.4 มีการจัดเตรียมสื่อ อุปกรณ์การสอน วัสดุ อุปกรณ์ปฏิบัติการต่าง ๆ ไว้เป็นอย่างดี (Having to prepare of teaching media and laboratory material.)							
3. เทคนิคและกลวิธีการสอน (Teaching technique)							
3.1 บ่งชี้ถึงวัตถุประสงค์หรือสิ่งที่จะได้รับจากการบรรยาย/การสาธิตเสมอ (Identifying of objective in lecture and demonstration.)							
3.2 สอนอย่างมีโครงสร้าง เป็นลำดับขั้นตอน (Having the steps and structure of teaching.)							
3.3 มีการสอนที่เน้นการเรียนรู้ร่วมกันระหว่างผู้เรียน (Teaching with emphasis on collaborative learning between learners.)							

List of Good teaching characteristics	Yes, certainly					Uncertain	Absolutely not
	5	4	3	2	1		
3.4 เปิดโอกาสให้ผู้เรียนซักถามทั้งในและนอกชั้นเรียน (Giving the opportunities for learner to ask the question, both inside and outside of classroom.)							
3.5 สนับสนุนให้ผู้เรียนมีส่วนร่วมในการอภิปราย (Facilitating the learner to participate in classroom discussion activity.)							
3.6 ส่งเสริมให้ผู้เรียนเกิดการเรียนรู้ ศึกษา ค้นคว้า และทดลองปฏิบัติได้ด้วยตนเอง (Supporting the learner to learn, searching, and experimenting by himself.)							
3.7 เสริมสร้างให้ผู้เรียนเกิดความมั่นใจในความรู้ความสามารถของตน (Supporting the learner to have confidence in knowledge and ability of himself.)							
3.8 ให้ข้อมูลย้อนกลับได้รวดเร็ว และเป็นประโยชน์แก่ผู้เรียน (Immediately responding of useful feedback for learner.)							
3.9 ใช้ข้อมูลเดิมและข้อมูลย้อนกลับให้เป็นประโยชน์ เพื่อการกำหนดแผนและเป้าหมายการเรียนรู้ให้เหมาะสม (Utilizing of previous data and feedback for planning and determine the objective learning.)							
3.10 ใช้ข้อมูลเดิมและข้อมูลย้อนกลับให้เป็นประโยชน์ การปรับปรุง วิธีการสอนให้เหมาะสมกับผู้เรียน (Utilizing of previous data and feedback for adapts teaching process that suitable for learner.)							
3.11 พูด บรรยายและนำเสนอด้วยน้ำเสียงที่ชัดเจน เป็นจังหวะ ระดับเสียงเหมาะสม และแสดงถึงความมั่นใจ (Presenting with the clear sound, has nice rhythm of speaking and showing of confident in lecture.)							
3.12 พูด บรรยาย/อธิบายได้อย่าง กระจ่างชัด ได้ใจความและมีเหตุมีผล (Explaining with clearly, rationality and concisely.)							
3.13 หลีกเลี่ยงการใช้ภาษาที่ยุ่งยาก/ภาษาสแลง (Avoiding use of complex word or slang word.)							
3.14 เขียนบรรยาย ถูกต้อง ชัดเจน เป็นระเบียบและอ่านง่าย (Writing to explaining is correct, clearly and easy to read.)							
3.15 สาธิต/แสดงตัวอย่าง ในการปฏิบัติการได้อย่างชัดเจน และเข้าใจได้ง่าย (Demonstration the practical process with clearly and easy to understand.)							
3.16 ให้ตัวอย่าง/สาธิตการปฏิบัติการที่ชัดเจน มีจุดเชื่อมโยงระหว่างทฤษฎีสู่การปฏิบัติ / ผลลัพธ์และบทสรุป (Providing the practical examples and demonstrate with clearly of linkage between theoretical, practical, experimental results and conclusion.)							
3.17 ให้ตัวอย่างมีความเหมาะสมกับระดับผู้เรียน ช่วยเสริมให้ผู้เรียนมีแรงจูงใจในการเรียน (Providing the example that suitable for ability and reinforce learner to learning.)							

List of Good teaching characteristics	Yes, certainly					Uncertain	Absolutely not
	5	4	3	2	1		
3.18 นำเสนอประสบการณ์การเรียนรู้ของท่าน ให้แก่ผู้เรียนเพื่อเป็นแบบอย่างแก่ผู้เรียน (Transferring of self-learning experience as role models for learner.)							
3.19 แนะนำ/สอดแทรกประสบการณ์จริงในขณะศึกษา ดูงาน หรือการออกปฏิบัติการภาคสนาม (Suggesting and insert the real experience in study activity or in field works.)							
3.20 ให้ตัวอย่างที่มีประโยชน์ที่จะสามารถนำไปประยุกต์ใช้ได้ในชีวิตประจำวัน (Providing the useful examples that can apply in real life.)							
3.21 มีทักษะการเขียนบันทึกที่มีประสิทธิภาพ ตรงประเด็นและเข้าใจได้ง่าย (Having skill to note taking in relevant issue and easy to understand.)							
3.22 มีการสรุปประเด็นเนื้อหา ในการบรรยายอยู่เสมอ (Having of a conclusion of lecture.)							
3.23 มีการบริหารจัดการเวลาในการสอนเนื้อหาต่าง ๆ ได้ดี (Having a good management of teaching time in each of topics.)							
3.24 ดูแลและควบคุมการสอนในชั้นเรียนขนาดต่าง ๆ ได้เป็นอย่างดี (Having ability to take care and control the teaching in the various class sizes.)							
3.25 ควบคุมกิจกรรม การนำเสนอ อภิปรายภายในชั้นเรียน ให้ตรงประเด็น และอยู่ในกรอบเวลา (Controlling of classroom activity e.g. presenting, discussion, etc. make it correspond with learning objective and in the time.)							
3.26 ทักษะบรรยาย/สาธิต และบุคลิกภาพที่ดึงดูดให้ผู้เรียนเกิดความสนใจในการเรียนได้ดี (Having skill that make demonstration and explanation are attractive which affect learners to pay attention to learn.)							
3.27 สนใจในรายละเอียดต่าง ๆ ที่อาจส่งผลต่อความผิดพลาดในการเรียนการสอน (Concern in teaching detail that affect to make mistakes in teaching.)							
3.28 สอดแทรกอารมณ์ขัน ลดความตึงเครียดในชั้นเรียน (Decreasing of seriously atmosphere of teaching with humor.)							
4. การวัดและประเมินผล (Assessment)							
4.1 ใช้ข้อคำถาม/วิธีการวัดที่เหมาะสมกับระดับของผู้เรียน (Using of questions and measurement methods that suitable with the ability of learner.)							
4.2 ใช้ข้อคำถาม/วิธีการวัดที่เสริมสร้างการเรียนรู้ เชิงวิเคราะห์ สังเคราะห์ (Using of questions and measurement methods that supported the student to have analytical and synthetic thinking.)							
4.3 ใช้ข้อคำถามในเชิงวินิจฉัย เพื่อช่วยระบุถึงจุดบกพร่องของผู้เรียน (Using diagnostic question to identify the weakness of learner.)							

List of Good teaching characteristics	Yes, certainly					Uncertain	Absolutely not
	5	4	3	2	1		
4.4 ใช้การบ้าน/งานมอบที่ส่งเสริมการขยายขอบเขตการเรียนรู้ (Providing assignments and homework that support the learner to extended their boundary of learning.)							
4.5 มีการวัดและประเมินผลอยู่อย่างสม่ำเสมอ (ก่อน, ระหว่าง, หลังเรียน) (Always having to measure and evaluate of learner (before, during and after teaching).)							
4.6 ประเมินผลที่สอดคล้องตามวัตถุประสงค์การเรียนรู้ของรายวิชา (Having the assessment that corresponds with the objective learning.)							
4.7 ประเมินผลอย่างละเอียดถี่ถ้วน ครอบคลุม ประเด็นความรู้ (Assessment with delicate and coverage of all important topic.)							
4.8 ประเมินผลเพื่อนำข้อมูลไปใช้บ่งชี้จุดบกพร่องที่ควรแก้ไข (Using information from assessment to indicate the weakness point of teaching and learning.)							
5. สื่อและอุปกรณ์การสอน (Materials)							
5.1 ปรับปรุง/แก้ไข เนื้อหา ความรู้ในสื่อและเอกสารให้มีความถูกต้อง ทันสมัยอยู่เสมอ (Always update, audit for correctness of contents in documentation for teaching.)							
5.2 สื่อการสอนและเอกสารประกอบการสอน มีคุณภาพ ชัดเจน อ่านง่าย (Having of high quality of teaching media and documents that clearly and easy to read.)							
5.3 ใช้เทคโนโลยีสารสนเทศ (สื่อและแหล่งข้อมูลอิเล็กทรอนิกส์) ได้อย่างเหมาะสม (Using of suitable Information technology (media and electronic resources).)							
5.4 ใช้บุคลากร (ผู้ช่วยสอน) ช่วยสนับสนุนการสอนได้อย่างเหมาะสม (Using Teaching Assistant to assist in teaching process in suitable manner.)							
6. **บุคลิกลักษณะ (Personality)**							
6.1 กระตือรือร้น ตั้งใจ และรับผิดชอบในการสอน (Having of enthusiasm, willingness and responsibility in teaching.)							
6.2 ให้เกียรติและเคารพในสิทธิของผู้เรียน (Providing of honor and respect the rights of learner.)							
6.3 มีความเป็นกันเอง ไม่ถือตน (Having a friendly and not haughty.)							
6.4 มีอารมณ์ขัน และมีจิตใจให้เบิกบานเสมอ (Having of humor and always joyfully.)							
6.5 มีความยุติธรรม และให้ความเสมอภาค (Having of justice and equality.)							
6.6 มีเมตตา กรุณา (Having benevolence.)							
6.7 มีความอดทน อดกลั้น (Having tolerated.)							

List of Good teaching characteristics	Yes, certainly					Uncertain	Absolutely not
	5	4	3	2	1		
6.9 มีระเบียบ สะอาด แต่งกายสุภาพ (Having orderly, clean and appropriate of dress.)							
6.10 มีมนุษยสัมพันธ์ที่ดี เปิดเผย พบปะสังคม (Having of good interpersonal skill, disclosure and social interaction.)							
6.11 ยอมรับความผิดพลาด และพยายามปรับปรุงแก้ไข (Admit a mistake and try to improve.)							
6.12 ทุ่มเท ในการสนับสนุน ช่วยเหลือให้ผู้เรียนที่ประสบปัญหาสามารถก้าวผ่านอุปสรรค (Dedicating to support and help learners who are obstacle in overcome those barriers.)							
6.13 มีปฏิสัมพันธ์ที่ดีภายในชั้นเรียนระหว่างอาจารย์และลูกศิษย์ (Having of good interaction of teacher and learner in classroom.)							
6.14 สนับสนุน ให้กำลังใจและเป็นแรงบันดาลใจแก่ผู้เรียนอยู่เสมอ (Providing of support, encouragement and inspiration to students regularly.)							
6.15 เข้าพบเพื่อพูดคุย/ขอคำปรึกษาได้ง่าย (Easy to found for conversation or asking for consult.)							
6.16 ให้คำแนะนำที่มีประโยชน์แก่ผู้เรียนที่ประสบปัญหา ทั้งในและนอกชั้นเรียน (Giving the useful advice to students who are facing the problems, both inside and outside the classroom.)							
6.17 มีใจกว้างเปิดรับข้อมูลและรับทราบความต้องการของผู้เรียน (Having generous, open mind to perceive information and requirement of learner.)							
6.18 ดูแล เอาใจใส่ อย่างทั่วถึง (เช่น การจดจำชื่อผู้เรียน หรือเรื่องราวที่เกี่ยวข้องกับผู้เรียนได้) (Thoroughly takes care and attention (i.e. can recognize the name of learner or memorize the stories of learner).)							

APPENDIX B

List of Initial Vocabulary of

Good Teaching Characteristics

LIST OF INITIAL VOCABULARY

OF GOOD TEACHING CHARACTERISTICS

SEED WORDS	Knowledge	Teaching preparation	Teaching techniques and strategies	Measurement and evaluation	Teaching media and materials	Personality
LIST OF NOUNS						
Ability			●	●		
Activity			●			
Adapts			●			
Administration			●			
Admit						●
Advice						●
Assessment				●		
Assignments				●		
Atmosphere			●			
Attention			●			●
Audit					●	
Avoiding			●			
Barriers						●
Benevolence						●
Boundary				●		
Care			●			●
Class			●			
Classroom			●			

SEED WORDS	Knowledge	Teaching preparation	Teaching techniques and strategies	Measurement and evaluation	Teaching media and materials	Personality
Colleague	•					
Concern			•			
Conclusion			•			
Confidence			•			
Contents		•			•	
Conversation						•
Correctness					•	
Coverage				•		
Data			•			
Demonstration			•			
Detail			•			
Disclosure						•
Discussion			•			
Document		•			•	
Documentation					•	
Dress						•
Emphasis			•			
Encouragement						•
Enthusiasm						•
Equality						•
Evaluation				•		
Examples			•			
Experience			•			
Explanation			•			
Feedbacks			•			
Field			•			

SEED WORDS	Knowledge	Teaching preparation	Teaching techniques and strategies	Measurement and evaluation	Teaching media and materials	Personality
Help						●
Himself						●
Honor						●
Human						●
Humility						●
Humor						●
Increase	●					
Information	●	●		●		●
Information technology					●	
Inspiration						●
Interaction						●
Issue			●			
Justice						●
Knowledge	●					
Laboratory		●				
Learner	●		●	●		●
Learning			●	●		
Lecture			●			
Life			●			
Linkage			●			
Management			●			
Manner					●	
Material					●	
Measurement				●		
Media					●	
Methods				●		

SEED WORDS	Knowledge	Teaching preparation	Teaching techniques and strategies	Measurement and evaluation	Teaching media and materials	Personality
Mind						•
Mistakes			•			
Models			•			
Name						•
Objective		•				
Obstacle						•
Opportunities			•			
Personal						•
Personality						•
Planning			•			
Point				•		
Preparation		•				
Principle	•					
Problems						•
Process			•			
Quality					•	
Question				•		
Rationality			•			
Relationship						•
Requirement						•
Research	•					
Resource		•			•	
Responsibility						•
Results			•			
Retain	•					
Rhythm			•			

SEED WORDS	Knowledge	Teaching preparation	Teaching techniques and strategies	Measurement and evaluation	Teaching media and materials	Personality
Rights						•
Role			•			
Sequence		•				
Size			•			
Skill			•			•
Slang			•			
Sound			•			•
Steps			•			
Stories						•
Structure			•			
Student	•			•		•
Study			•			
Subject	•					
Support				•		•
Teacher						•
Teaching			•			
Teaching assistant				•		
Technique			•			
Thinking				•		
Thoroughly						•
Time			•			
Topic			•	•		
Transfer			•			
Use			•			
Weakness				•		
Willingness						•

SEED WORDS	Knowledge	Teaching preparation	Teaching techniques and strategies	Measurement and evaluation	Teaching media and materials	Personality
Word			●			
Works			●			
LIST OF VERBS						
Affect			●			
Answer	●					
Applied			●			
Are						●
Asking						●
Assist					●	
Centered			●			
Clarity		●				
Consult						●
Control			●			
Controlling			●			
Correspond				●		
Decreasing			●			
Dedicating						●
Demonstrate			●			
Determine			●			
Evaluate				●		
Experimenting			●			
Explaining			●			
Extended				●		
Facilitating			●			
Facing						●
Finding	●					

SEED WORDS	Knowledge	Teaching preparation	Teaching techniques and strategies	Measurement and evaluation	Teaching media and materials	Personality
Found						●
Giving						●
Has			●			
Having			●			
Help						●
Home works				●		
Identifying			●			
Improve						●
Indicate				●		
Insert			●			
Learn			●			
Make			●			
Measure				●		
Memorize						●
Note taking			●			
Overcome						●
Participate	●		●			
Pay			●			
Perceive						●
Prepare		●				
Presenting			●			
Providing			●			●
Read			●		●	
Recognize						●
Reinforce			●			
Respect						●

SEED WORDS	Knowledge	Teaching preparation	Teaching techniques and strategies	Measurement and evaluation	Teaching media and materials	Personality
Responding			●			
Searching			●			
Showing			●			
Speaking			●			
Suggesting			●			
Supporting			●			
Take			●			
Transferring			●			
Try						●
Understand	●					
Update					●	
Using				●	●	
Utilizing			●			
Writing			●			

CURRICULUM VITAE

Mr. Somjin Phiakoksong was born on December 26, 1977 in Nakhon Ratchasima Province, Thailand. He received Bachelor of Measurement and Evaluation in Education from Nakhon Ratchasima Ratchabhat University. In 2008, he got a potential graduate scholarship and received Master of Information Science from Suranaree University of Technology, Thailand in 2010. In 2011, he pursues his doctoral degree in Information Technology Program at Suranaree University of Technology. His major research interests are in Statistical analysis, Knowledge management and Data and text mining.