

# Emerging Patterns in Student's Learning Attributes through Text Mining

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## ABSTRACT

Text mining has been used in various fields including education. Using unsupervised sentiment analysis combined with a clustering algorithm, we discovered 2 emerging clusters of learning characteristics (traditional (T) and experiential (E)), and correlations among learning attitudes such as motivation, peer relationship and positive attitude. We found a positive correlation between social learning and peer relationship ( $p < 0.005$ ), but negative between social learning and negative attitude ( $p < 0.05$ ) in E. Social learning was positively correlated with positive attitude ( $p < 0.001$ ) in T.

## Keywords

Text mining, clustering algorithm, sentiment analysis, motivation, engagement

## 1. INTRODUCTION

Studies have shown that attitudes are related to motivation, engagement and outcome in learning. When learners have positive attitude, they would spend more time engaging in learning [5, 9]. Difference in students with positive attitude and motivation in e-learning settings was observed [6]. Students with boredom have poorer learning outcome than those with frustration [1]. Hence, sentiment analysis could be used to harness learning attitudes.

Recently, machine learning methods in natural language processing have become prevalent, while there are many training datasets for supervised learning algorithms. However, the task of opinion mining without such dataset can be a challenge. We combined one symbolic technique for an unsupervised machine learning with clustering algorithm to discover emerging patterns among texts written in *Thai* that could reflect student's learning attitudes. Our findings demonstrated how such approach could be useful in exploring and understanding relationships among learning attitudes.

## 2. METHODS

### 2.1. Data Acquisition

Our subjects were 83 freshman undergraduate students (M:F = 62:21) (average age = 17.2) in Robotics and Automation Engineering, at King Mongkut's University of Technology Thonburi. They consented to participate in the study.

This data set was collected while students were taking same classes. Students wrote in *Thai* about what they learned each week for all 14 weeks.

### 2.2. Data Analyses

We used an open source Lexitron dictionary (NECTEC, 2006) as word database in *Thai* and an open source algorithm Lexto (NECTEC, 1994) to tokenize texts into longest words possible. We had 383 entries. On average, each entry had 124.3 words.

Word frequency was calculated for each student as the ratio of the number of times each unique word appeared in any learning journal and the total number of words appeared. Irrelevant words (prepositions, conjunctions, and generic verbs and nouns) or words that appeared less than 20 times in all entries were filtered out. Negation and irrealis phenomena, out-of-topic sentences, or irony and sarcasm were not treated in our analysis. We performed several clustering algorithms on the distance matrix with various initial conditions and different number of clusters (2, 3, or 4) to determine if any pattern of word clusters could emerge.

Among frequently-used words, instructors chose words that represented these six attitudes: 1) positive relationship with others (Peer relationship), 2) desire to improve oneself (Motivation), 3) positive emotion (Positive attitude), 4) negative emotion (Negative attitude), 5) engagement in learning on one's own (Solitary learning), and 6) engagement in learning that involves others (Social learning). The associated words were also evaluated by another group of students to indicate levels of congruity of each attitude<sup>2</sup>. The results are shown in Table 1. We calculated a student's attitude score to be the sum of percentage of word frequency for each word associated with each of the 6 attitudes. Pearson correlation coefficient and p-value of the correlation were computed between any two attitudes. Correlation analyses were performed independently for each cluster.

## 3. RESULTS AND DISCUSSION

We found that 2 clusters emerged, yielding the most consistent set of words. The first cluster contained words such as take exams, read books, problem sets, formula, lessons, math, writing, calculus, physics, language, etc. The second contained words such as human being, people, work, see, team, fun, talk, play, like,

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<sup>2</sup> The data were collected from 28 native Thai speakers (average age = 20.18). They were asked to rate how each pair of words and an attitude was meaningfully or semantically related (e.g. Peer Relationship vs. Group) in a 5-point Likert scale.

group, together, etc. The first cluster was labelled T for traditional and the second, E for experiential. Although initial conditions and clustering algorithms were varied, these two clusters emerged.

**Table 1. Words Associated with 6 attitudes and their rating<sup>3</sup> (mean score and standard deviation in parentheses)**

Attitude	Associated Words	Rating
Peer Relationship	group, talk, help, together, team, help each other, we, everyone, etc.	3.87 (0.48)
Motivation	improve, practice, better, goals, development, improvement, etc.	3.76 (0.4)
Positive Attitude	fun, enjoy, like, happy, funny, good, excited, etc.	3.64 (0.37)
Negative Attitude	stressed, confused, sleepy, slow, difficult, do not understand, etc.	3.01 (0.45)
Solitary Learning	exams, formula, scores, books, grades, study, responsibility, etc.	3.34 (0.77)
Social Learning	hands on, experiment, project, communication, participate, etc.	3.71 (0.31)

Motivation was positively correlated with solitary learning ( $R=0.4$  (T) and  $0.55$  (E);  $p<0.05$ ). It could mean that for T, when one desires to improve oneself, one engages in learning even on one's own. Our result supports a previous finding that motivation and engagement were correlated [3, 10]. Such correlation for E might be because when one enjoys learning with others, their motivation increases. Previous studies showed that people who reported feeling happy were engaged in social activities more often and that sociability was a strong predictor of life satisfaction [2, 7].

Additionally, for E, motivation was positively correlated with social learning ( $R=0.42$ ,  $p<0.05$ ); social learning was positively correlated with peer relationship ( $R=0.6$ ,  $p<0.005$ ), but negatively correlated with negative attitude ( $R=-0.44$ ,  $p<0.05$ ). For T, social learning was positively correlated with positive attitude ( $R=0.55$ ,  $p<0.001$ ). Relationships with peers are very important in helping learners become adaptive in different learning environments [8]. Previous studies showed that students with positive peer relationship were likely to be engaged in academic tasks and perform better in school than students without positive peer relationships [11, 12, 13]. Our finding supports existing literature that learning abilities are related to attitude of learners [5].

However, our approach has some limitations. Our algorithm is a simple frequency counting. However, since less frequently used words have been filtered out, we expected that our results would still be robust even with different weighting methods. Moreover, no sarcasm, negation or unrealistic phenomena were considered. This might have a slight effect on our results.

Future work involves testing robustness of our approach with more data. To explore additional emergence, we could also apply

adjustments to various clustering algorithms [4]. We are developing a platform to help teachers quantify student's attitudes.

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<sup>3</sup> For rating, a five-point score means strongly agree and an one-point score means strongly disagree.