International Journal of Business, Human and Social Sciences
ISSN: 2517-9411
Vol:10, No:2, 2016

An Analysis of Learners' Reports for Measuring Co-Creational Education

Takatoshi Ishii, Koji Kimita, Keiichi Muramatsu, Yoshiki Shimomura

***Abstract*—**To increase the quality of learning, teacher and learner need mutual effort for realization of educational value. For this purpose, we need to manage the co-creational education among teacher and learners. In this research, we try to find a feature of co-creational education. To be more precise, we analyzed learners' reports by natural language processing, and extract some features that describe the state of the co-creational education.

***Keywords*—**Co-creational education, e-portfolios, ICT integration, labeled Latent Dirichlet allocation.

I. Introduction

IN service science field, the service defined as the application of specialized competences (knowledge and skills), through deeds, processes, and performances for the benefit of another entity or the entity itself [1]. Therefore, we can consider higher education as a service. From the viewpoint of services, learners in higher education institutions can be regarded as customers, and teachers can be regarded as service providers. The value of a service is perceived by the customer on the basis of value in use [1]. In addition, the value in use is co-created by customers and providers [1]. In this view, the value of an education also needs to be determined by learners, and this value is created by cooperation among learners and teachers. Therefore, teachers need to know how to encourage the co-created educational value.

In this research, we try to find a feature of co-creational education from learners' reports. The report is often used assignment in Japanese university. In the reports, learners write their thinking about the subject that is imposed by teachers. Thus, the reports reflect learners' state such as thinking process, understanding, and writing skill. On this site, [2] proposed the learning system for report writing. In this system, the learners are recommended other learners reports, and brings various viewpoints to learners. From this, learners can cultivate a better understanding and revise their reports. In the same site, this article seeks a feature of co-creational education from learners' reports. To be more precise, we analyzed learners' reports by LLDA that is one of natural language processing methods. LLDA can extract contents (theme) from documents. Our main idea is to extract features of co-creational education from the contents of learners' reports. For this purpose, we analyze actual learners' reports, and find feature of feature of learners with co-creational education.

Takatoshi Ishii, Koji Kimita, and Yoshiki Shimomura are with the Tokyo Metropolitan University, Asahigaoka 6-6, Hino-shi, Tokyo, Japan (e-mail: t_ishii@tmu.ac.jp, kimita@tmu.ac.jp and yoshiki-shimomura@center.tmu.ac.jp).
Keiichi Muramastu is with Saitama University, Shimo-Okubo 255, Sakura-ku, Saitama-shi, 338-8570 Japan (e-mail: muramatsu@mech.saitama-u.ac.jp).

II. Analysis of Co-Creation in Learning

In this research, we seek a feature of co-creational education, to measure it. The first, this section introduces the view for evaluating co-creational education.

A. Co-Creation Value in Learning Service

Toya [3] defined co-creation value of a service as the three types of value: Fundamental Value (FV), Knowledge Value (KV), and Emotional Value (EV).

FV is the value which is created by committing fundamental function that is promised by customers and providers. In higher education, we can consider FV as achieving learning goals in the syllabus or Rubric.

KV is the value for receiving or providing the service smartly. When customers receive the service, the customers gradually understand how to receive good service. On the other hand, providers gradually understand how to provide good service. KV means the value of these skills or getting knowledge. In higher education, KV is considered as the understanding how to learn / teach for better. The examples of KVs for learners are preparing the lecture, and asking questions to solve that.

EV is the value of good emotion (ex, happiness, satisfaction, motivation) with customers and providers. In higher education, the high satisfaction and motivation for the lecture are ones of EV.

B. Analysis of Co-Creation in Learning

For observing co-creational education, we analyzed an actual lecture. We analyzed learners' action, learners' motivation, and contents of learners' reports for the lecture. We assume that the learners with co-creation learning have high FV, KV, and EV. In this analysis, we focus on KV and EV. (FV contains personal information. For this reason, we could not access FVs.)

Fig. 1 shows the image of this analysis. The first step gathered the learner's reports, and found the learner with co-creational education by checking KV and EV. By using text mining, the next step analyzed the contents within the reports for describing concretion learning. The final step interpreted the result of text mining.

C. Details of Reports

We analyzed an actual lecture that was conducted in Tokyo Metropolitan University in 2015. The target lecture is for undergraduate students in engineering department. The lecture was given for design engineering. In this lecture, students learned about environmental burden and its evaluation by using evaluation software. The students evaluated environmental burden of their familiar products, and reported that result. Each report was created by 2~3 students. The total number of students is 33.

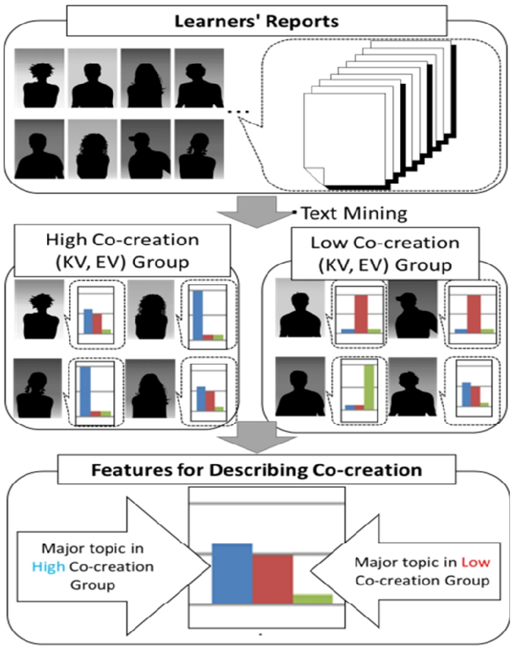

Fig. 1 Image of analyze

Please put check your actions with this lecture	
☐	Attending
☐	Doing homework
☐	Writing down important to note
☐	Do not be late
☐	Review for the lecture
☐	Asking the question to the teacher for solving question.
☐	Understand utility of learned object
☐	Investigating the question by yourself.
☐	Ask the question to the friends for solving question.
☐	Responce for questioning
☐	Understand the learning goal
☐	Understand the relevance of each lecture theme
☐	Telling your friends to solve friends question.
☐	Seeking improvement for the blackboard.
☐	Preparing the lecture
☐	Seeking the improvement for speech (voice, magnitude, etc)
☐	Seeking the improvement for progress of the lecture
☐	Other

* In fact, this questionaire written in Japanese for Japanese students.

Fig. 2 Questionnaire Items for measuring KV

D. Measurement for Evaluating KV

For evaluating KV, we constructed a questionnaire that asked what actions the learners did for the lecture. For constructing the questionnaire, we gathered the actions expected by the teacher who conducted the lecture. Fig. 2 shows this questionnaire. The questionnaire contains a question: “please put check your actions that are done for the lecture”.

In this article, the learner with higher KV was defined as the learners that have upper half score (the number of checks) of the questions.

E. Measurement for Evaluating EV

For evaluating EV, this analysis employed ARCS model [4] that measure the interest for educational materials. The learner with high EV was defined as the learners that have an upper half score in the learners.

F. Analysis Method for Report Contents

To analyze the reports, this article employed a text mining method called LLDA [5] that is one of topic models. The topic model is a statistical model for discovering the abstract "topics" that occur in a collection of documents. Topic model is a method for clustering documents based on the topics (subjects or contents) in the documents. Labeled Latent Dirichlet Allocation (LLDA) model [5] estimates topics of the documents, and clustering the documents based on estimated topics. LLDA assumes the document includes multiple abstract “topics” that are subject or contents of the documents. And the topics correspond to the labels. LLDA estimates the topics of each word from the bias of word frequency in the documents and labels with the documents. By aggregating the topics of words in the document, LLDA estimates the topic allocation of each label.

For analyzing correspondence between KV (EV) and contents, we put the label of "KV (EV)-High" or "KV (EV)-Low" to each report. From these data, LLDA can extract what words characterize the label: “KV (EV)-High” and “KV (EV)-Low”.

III. Result

A. Result for KV Label

We conducted two analyses that different on assumption.

First, we assume there were only two topics that related to “KV-High” and “KV-Low”. In other words, each word in reports should have relation with either KV-High or KV-Low.

Table I shows the result of this analysis. Table I lists representative word (sorted by relevance, top word is most relevant) for “KV-High” and “KV-Low”. From Table I, we could not find major difference, but the number of product names (painted grey in Table I) in “KV-High” topic was less than one in “KV-Low” topic. This might be related to the contents in the lecture. In the lecture, the teacher introduced about Product Service System: PSS. PSS is also known as a function-oriented business model. By combining products and service, PSS provides more choose for business, and lead high added value. Thus, this result might interpret that “KV-High” learners have a part of way for PSS thinking.

TABLE I
RELATED WORDS TO "KV-HIGH" AND "KV-LOW"

KV-High(Topic1)	KV-Low (Topic2)
recycling	consumption
Evaluation	Figure
incineration	Manufacturing
figure	Power
damage	refrigerator
process	mobile pone
result	milca (the name of using software)
Consideration	microwave oven
Report	life cycle
change	Earth
graph	Printer
Ecology	Origin
output	stage
Copy	Discharge
Human	Air conditioner
Target	Impact
Light car	Year
factory	Automobile
resource	conditions
Comparison	Warmth
service cycle	process
aircraft	fossil
Configuration	
Diversity	

TABLE II
RELATED WORDS TO "KV-HIGH", "KV-LOW" AND "OTHERS"

KV-High(Topic1)	KV-Low(Topic2)	Others(Topic3)
recycling	refrigerator	Automobile
incineration	Power	environment
figure	microwave oven	Manufacturing
Evaluation	mobile phone	Company
process	life cycle	consumption
change	stage	Disposal
Ecology	use	Printer
damage	milca (the name of using software)	Figure
Report	Origin	pc
Copy	Cause	Earth
Creature	Impact	system
factory	fossil	Product
result	Year	Discharge
resource	conditions	design
Consideration	oxidant	Passenger car
Human	Photochemistry	load
output	example	Air conditioner
Diversity	crude oil	engineering
cycle	Creating	Photosensitive
aircraft	Loading	Light car
Comparison		Occupy
Configuration		
graph		
A process		
Reduction		

Next, we assume there were three topics: related to "KV-High" and "KV-Low", not related KV score. In other words, each report has "KV related topic" and "not related topic (Other)". Tables II and III show the results of this analysis. Table II lists representative words for "KV-High", "KV-Low" and "Others". Table II had a tendency similar to Table I. The number of product names (painted grey in Table II) in "KV-High" topic was less than one in other topics. Moreover, Table II shows that the product names appeared in "KV-Low" and "Others" topics as the most relevant words. Therefore, it might interpret that "KV-High" reports have less number of product names.

Table III shows estimated topic allocation (rate) for each report. In Table III, the cells with Top 10% values are painted grey. From Table III, we can understand what topics appear in the reports. For example, the column of ID05 shows that ID05 report has 72.5% of "KV-Low" topic, and 27.5% of "Others" topic. From Table III, most report have "Others" topic and that topic allocation was highest in the allocation. Therefore, this might show that in many cases, the topic in the reports did not relate to KV score.

TABLE III
TOPIC ALLOCATION IN THE REPORTS

ID	KV-High(Topic1)	KV-Low(Topic2)	Others(Topic3)
ID01	100.0%	0.0%	0.0%
ID02	100.0%	0.0%	0.0%
ID03	0.0%	0.0%	100.0%
ID04	0.0%	1.6%	98.4%
ID05	0.0%	72.5%	27.5%
ID06	0.0%	0.0%	100.0%
ID07	0.0%	0.0%	100.0%
ID08	0.0%	8.7%	91.3%
ID09	0.0%	0.0%	99.9%
ID10	0.0%	0.0%	100.0%
ID11	0.0%	99.9%	0.0%
ID12	100.0%	0.0%	0.0%
ID13	0.0%	56.8%	43.2%
ID14	0.0%	75.4%	24.6%
ID15	0.0%	99.9%	0.0%
ID16	0.0%	0.0%	99.9%
ID17	0.0%	69.3%	30.7%
ID18	0.0%	0.0%	100.0%
ID19	100.0%	0.0%	0.0%
ID20	0.0%	0.0%	100.0%
ID21	0.0%	0.0%	99.9%
ID22	0.0%	0.0%	100.0%
ID23	8.4%	0.0%	91.6%
ID24	0.0%	0.0%	99.9%
ID25	0.0%	0.0%	100.0%
ID26	0.0%	99.9%	0.0%
ID27	0.0%	0.0%	99.9%
ID28	0.0%	0.0%	99.9%
ID29	0.0%	0.0%	100.0%
ID30	100.0%	0.0%	0.0%
ID31	100.0%	0.0%	0.0%
ID32	0.0%	0.0%	100.0%
ID33	0.0%	0.0%	100.0%

B. Result for EV Label

TABLE IV
RELATED WORDS TO "EV-HIGH" AND "EV-LOW"

EV-High(Topic1)	EV-Low(Topic2)
Evaluation	Discharge
figure	refrigerator
resource	stage
damage	Product
recycling	Mobile phone
incineration	consumption
process	PET bottles
Configuration	microwave oven
Report	Phone
Diversity	Passenger car
graph	the purpose
Comparison	Impact
health	Origin
factory	milca (the name of using software)
Copy	transport
Numerical value	Example
Manufacturing	Light car
Automobile	environment
material	Power
output	Ecology
Human	life cycle
use	Calculation
change	
A process	
other	
Need	

TABLE V
RELATED WORDS TO "EV-HIGH", "EV-LOW" AND "OTHERS"

EV-High(Topic1)	EV-Low(Topic2)	Others(Topic3)
figure	refrigerator	Automobile
Evaluation	Mobile phone	Figure
incineration	Discharge	Printer
process	microwave oven	Manufacturing
recycling	PET bottles	Earth
damage	Ecology	Impact
resource	Case	Warmth
Copy	production	pc
Report	life cycle	Disposal
factory	Reduction	Air conditioner
change	stage	consumption
output	Origin	Evaluation
Diversity	Correction	use
Comparison	the purpose	Occupy
cycle	Product	Photosensitive
aircraft	disposal	Light car
Consideration	mass	copper
Numerical value	specification	Assignment
A process	conditions	oil
Synthesis	Tokyo	Reduction
Operating	result	Company
use		material
health		parts
		create
		usually
		material

We conducted two analyses with the same assumption as the previous section. In the same context as the previous section, first we assume there were only two topics that related to "EV-High" and "EV-Low". In other words, each word in reports should have relation with either EV-High or EV-Low.

Table IV lists representative words for "EV-High" and "EV-Low". From Table IV, we can find the similar tendency as the result of the previous analysis. The number of product names (painted grey in Table IV) in "EV-High" topic was less than" EV-Low" topic.

Then, we conducted an analysis for three topics: "KV-High", "KV-Low", and "Others". Tables V and VI show this result. Table IV lists representative words for "EV-High", "EV-Low" and "Others". In Table IV, there is the tendency similar to Tables I, II and IV. The number of product names (painted grey in Table V) in "EV-High" topic was less than one in other topics.

TABLE VI
TOPIC ALLOCATION IN THE REPORTS

ID	EV-High(Topic1)	EV-Low(Topic2)	Others(Topic3)
ID01	100.0%	0.0%	0.0%
ID02	100.0%	0.0%	0.0%
ID03	0.0%	0.0%	100.0%
ID04	0.0%	0.0%	100.0%
ID05	0.0%	63.2%	36.8%
ID06	0.0%	0.0%	100.0%
ID07	0.0%	8.1%	91.9%
ID08	0.0%	72.7%	27.3%
ID09	0.0%	0.0%	100.0%
ID10	0.0%	0.0%	100.0%
ID11	0.0%	100.0%	0.0%
ID12	100.0%	0.0%	0.0%
ID13	0.0%	0.0%	100.0%
ID14	0.0%	100.0%	0.0%
ID15	0.0%	100.0%	0.0%
ID16	0.0%	0.0%	100.0%
ID17	0.0%	74.9%	25.1%
ID18	0.0%	0.0%	100.0%
ID19	100.0%	0.0%	0.0%
ID20	0.0%	0.0%	100.0%
ID21	0.0%	0.0%	100.0%
ID22	0.0%	0.0%	100.0%
ID23	0.0%	0.0%	100.0%
ID24	0.0%	100.0%	0.0%
ID25	0.0%	0.0%	100.0%
ID26	0.0%	100.0%	0.0%
ID27	0.0%	100.0%	0.0%
ID28	0.0%	0.0%	100.0%
ID29	0.0%	0.0%	100.0%
ID30	0.0%	100.0%	0.0%
ID31	0.0%	100.0%	0.0%
ID32	0.0%	100.0%	0.0%
ID33	0.0%	100.0%	0.0%

Table VI shows estimated topic allocation (rate) for each report. In Table VI, the cells with Top 10% values are painted grey. From Table VI, about half of the reports have "Others" topic and that topic allocation was highest in the allocation.

TABLE VII
NUMBERS FOR KV LABEL AND TOPICS INDICATED TOPICS

		Indicated KV-Score by LLDA			Total
		KV-High	KV-Low	Others	
Label	KV-High	5	0	12	17
	KV-Low	0	6	9	15
	Missing	1	0	0	1
Total		6	6	21	33

TABLE VIII
NUMBERS FOR EV LABEL AND TOPICS INDICATED TOPICS

		Indicated EV-Score by LLDA			Total
		EV-High	EV-Low	Others	
Label	EV-High	3	0	9	12
	EV-Low	0	9	4	13
	Missing	1	4	3	8
Total		4	13	16	33

IV. DISCUSSION

In comparison to Table III, most reports had relevance to EV score. To be more precise, we can consider the rate of conditional probability. Tables VII and VIII list the number of reports for KV (EV) label and topics indicated by LLDA.

From Table VII, the rate of true KV-High when LLDA indicates KV-High (precision) is 5/6 = 83%. And, when the report labelled KV-High, the rate of estimated KV-High by LLDA (recall) is 5/17 = 29%. In the same way, EV-High precision is 75%, recall is 25%. And more, KV-Low precision is 6/6 =100%, recall is 6/15 = 40%, EV-Low precision is 9/13 = 69%, recall is 9/13 = 69%. From those results, EV-Low is easily estimated than other scores from the reports. Because, when the report labelled KV-Low, the rate of estimated KV-Low by LLDA (recall) is 69% that is the highest rate in another one. In addition, KV-Low (EV-Low) is easily estimated than KV-High (EV-High). This result shows that, there are not many topics in report for estimating KV (EV) = high, but there are some topics in report for estimating KV (EV) = low. Therefore, the topics in the reports might estimate low co-creational education.

V. CONCLUSION

This article found a feature of co-creational education. To be more precise, we analyzed learners' reports by using natural language processing, and extract a feature. The reports written by the learner with low co-creational education contain many product names. Therefore, the report contents might be used to measure the case of the learner does conduct bad co-related education. Because the number of data for analysis is small, this result is not accurate. And this result might not be stable for general lecture. In general, the report contents are affected by lecture contents. Future work will contain verification of the result by analyzing large scale data.

ACKNOWLEDGMENTS

This research is supported by Service Science, Solutions, and Foundation Integrated Research Program (S3FIRE), Research Institute of Science and Technology for Society (RISTEX), Japan Science and Technology Agency (JST)

REFERENCES

[1] R. Robert, F. Lusch, Stephen L. Vargo, Service-Dominant Logic: Premises, Perspectives, Possibilities, Cambridge University Press, 2014.
[2] Y. Kato, T. Ishii, Y. Miyazawa, M. Ueno, Reports Recommendation System Based on Latent Dirichlet Allocation, the journal of Institute of Electronics, Information and Communication Engineers(IEICE), Vol. J99-D (2), pp.-, 2016, (in Japanese) (in printing).
[3] K. Toya, A study on the structure of the service co-creation value. Marketing Journal. Vol. 33(3), pp.32-45, 2014, (in Japanese).
[4] Keller, J. M. Approach, Motivational Design for Learning and Performance: The ARCS Model. Springer, 2014.
[5] D. Ramage, D. Hall, R. Nallapati, and C. D. Manning. 2009. Labeled LDA: a supervised topic model for credit attribution in multi-labeled corpora. In Proceedings of the 2009 Conference on Empirical Methods in Natural Language Processing: Vol. 1, pp. 248-256, 2009.