Development of a Trajectory Model for Visualizing Teacher ICT Usage Based on Event Segmentation Data

Longwei Zheng
lwzheng@dec.ecnu.edu.cn

Rui Shi
yyshirui@163.com

Bingcong Wu
648780962@qq.com

Xiaoqing Gu
xqgu@ses.ecnu.edu.cn

Yuanyuan Feng
yyfeng@fl.ecnu.edu.cn

East China Normal University
Shanghai, China, 200062

ABSTRACT
The adoption of educational technologies such as e-textbook has offered a new opportunity to gain insight into teachers' usage of ICT (Information and Communication Technologies). In the e-textbook platform, customized digital products and the learning activities organized in digital environment require teachers to make greater efforts in planning lessons and producing resources. In addition, usage of technology can vary greatly from one group of teachers from another in various contexts. In this study, we demonstrate how computations like event segmentation and contextual numbers can be exploited in visualizing trajectories of teacher's ICT usage. We also study with the experience structure via the implicit patterns within the raw data of an e-textbook platform. Such automated visual characterization might be helpful to the wide and scalable application of teaching analytics to represent teacher's ICT usage.

Keywords
Visual analytics; teaching analytics; contextual numbers; ICT

1. INTRODUCTION
Information and Communication Technologies (ICT) are becoming increasingly pervasive in education [12] and are making a difference in the ways teacher plan lesson and organize activities [13]. It is also well documented that teachers need support to make effective use of information technology in their teaching, because the incorporation of ICT is not easy process which involves many technical complexities [10]. With a goal of better use of ICT, teaching analytics is conceived as an analytics approach that focuses on the design, development, evaluation of visual analytics methods and tools for teachers [20].

However, the crucial step of supporting teacher interventions based on learning analytics insights remains under-supported [17]. As it often happens elsewhere in learning analytics, most learning environments are not designed for data analysis and mining [8], even if they do analysis, they are designed to focus on analyzing student learning or behavior and provide feedback to the teacher [1,20], not to analyze and represent the teacher's data they store. Therefore, many studies depict learning analytics for teachers rather than analytics about teaching [17].

In addition, although much work has been done on visualizing analytics result, their design and use is less understood, which can lead to the weak implementation as a result of promoting ineffective feedback [21,19,3]. In many cases, however, it is not easy to compare the complex objects over high dimension visualization which requires users to understand the semantics of visual representation and feature that are assumed by model and algorithm. Besides that, some visualization approaches present the narrow scope of the representation, as focused on one snapshot of a certain topic of data for a certain period time. It usually did represent several aspects of dataset that occurring within the environments but did not represent the nature of connections inside the datasets and provide a global view of usage [2]. As a consequence, the application of dashboards requires additional information processing in various work.

The purpose of this study is to design a computational procedure based on behavior data with the intent to create a visualization of trajectory that will help describe teacher ICT usage.

To explore these issues, we make a case study in which the data is gathered from an e-textbook server without any additional sensor or APIs. In previous study [23], we found that a segmentation method is effective in effort to provide features distilled for predicting e-textbook adoption in early days. In this study, we bring together event segmentation and one-dimension *Self-organizing map* to integrate an authentic teaching experience involving digital environment with embedded robust and continuous characterizing of ICT usage trajectories. The raw data records which were created in a e-textbook platform will be computationally transformed and displayed, so that teachers and other stakeholders can utilize the information of result of contextual visualization to get insights and improve dynamic and diagnostic decision-making.

2. DATA
We investigated issues within the context of data from an e-textbook platform named *ZoomClass*. *ZoomClass* includes a web-based authoring environment and an iPad application for teachers. Teachers were given access to customize all digital content for specific teaching objectives. They typically create courses, upload media resources and products which are mostly customized by themselves in other tools (such as PowerPoint), design tasks, assign activities, and insert quizzes on the web-based environment before class. Also, they can record and upload photos and videos by iPad application. The users of *ZoomClass* are teachers and students at a primary school of Shanghai. We obtained data on teacher authoring action records and student response action records, for 110 teachers enrolled in this e-textbook platform, observed over more than 5 semesters since 2014 October. Until January 2017, the teachers have performed a total of 117,324 actions, created 4,653 courses, uploaded 16, 901 digital resource included almost 9,000 image products and get 3,364,533 responses from students.

Figure 1. The iPad application *ZoomClass*

3. METHOD

In this study, we bring together an event segmentation algorithm and a nonparametric mapping which is called contextual numbers, to integrate an authentic teaching experience involving e-textbook platform with embedded continuous characterizing of ICT usage trajectories. In general, the intent of event segmentation is to determine how a threshold should be set automatically when partitioning action streams into usage feature spaces. And the approach of contextual numbers is used to map the high dimensional space of usage to a continuous one-dimensional numerical field, which are ordered in the given context, similar numbers refer to similar high dimensional states of usage. Figure 2 shows the computational procedure and associated steps, which will be discussed in detail in this section.

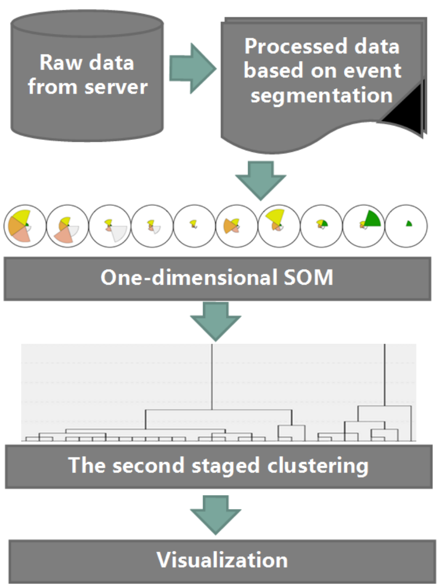

Figure 2. The computational procedure and associated steps

3.1 Event Segmentation

In our study, data comes from the raw records of an e-textbook platform. Two characteristics of this data are contained: 1. Data only recorded by the back-end server without any sensor embedded in front-end, that means the grain size of our data is much bigger when comparing with the sensor data (such as clickstream); 2. Multi-platform operation, which would cause the break off of data capturing when teacher transfer to another platform. Thus, these two problems lead to an amount of missing action data among our data set. In considering of this issue, an event segmentation method is introduced to transform action records to event dataset.

Event segmentation is a method means dividing a given number of observation into subsets with statistical characteristics that are similar within each subsets and different between subsets [4]. In this study, the goal of event segmentation is to automatically partition teacher actions into separate events, the segmentation method is only based the date time information of server log records. We consider action records in chronological order such that

$$R = \{R_1, \dots, R_m\} \tag{1}$$

where R_i is the ith action record in data set R with length m. A event segment $e_{i,j}$ which is a subset of R can be given as

$$e_{i,j} = \{R_i, \dots, R_j\}, \ \ 1 \le i \le j \le m \tag{2}$$

Intuitively, the time differences between inter-action records in an event are typically smaller than time differences between inter-action records from separate events, so the time intervals between observations are often considered as a criterion to judge partitioning [11].

With respect to the fact that teachers with various contexts have different usage of e-textbook, it is very likely that teachers perform diverse action frequencies during different period. Zheng and colleagues [24] developed an analysis method to discover the user water behavioral habits, in their invention, a novel continuous event segmentation algorithm based on threshold optimization was created to automatically separate the water usage records into multiple individual bath events for each user, this study employed a similar method to create features from teachers' action record data sets. In the event segmentation algorithm created by Zheng et al., a threshold of time difference has been used to determine whether consecutive action records are in a same event. The algorithm consists of following steps: 1. Compute inter-action intervals; 2. Compare every interval to the threshold of time difference. In step 2, If the interval is smaller, these two inter-actions are considered in a same event, if the interval is greater, they are divided into two different events. The algorithm will run through all of inter-action intervals, then we can obtain individual events from action log sets. An automatic threshold optimization model was developed to search the optimal threshold value to segment event.

The threshold optimization of each teacher in one week consists of following steps: 1. Segment events with successively varying thresholds, a fixed time delta d is set between two successive thresholds, we consider this threshold set in chronological order such that

$$TS = \{ts_1, ts_2, ts_3 \ \dots\} \tag{3}$$

2. Compute event number y for each threshold ts; 3. Specify minimum rate of event numbers' change for optimal threshold detection. In step 3, optimization algorithm uses a sliding window with a fixed size. The window can only contain n points, beginning at the current point and ending right before the next identified point. The optimization tries to find a possible starting point which is followed with a sequence of almost unchanged points. Suppose the threshold of the current point is ts_j, the average rate of event numbers' change cr is defined as follows:

$$cr(ts_j) = \frac{1}{n}\sum_{i=j}^{n}\left|\frac{y_i - y_{i+1}}{d}\right| \tag{4}$$

the final optimal threshold can be selected from given threshold set as follows:

$$ot(TS) = \text{Argmin}_i(cr(ts_i)) \quad (5)$$

Figure 3 shows an example of an event segmentation with varying thresholds. Here, the number of events declines rapidly when threshold is smaller than 10 minutes, it implies most inter-action intervals of the teacher are smaller than 10 minutes. And there is a significant possibility to separate an individual event into two or more sub-events if a small value is determined as threshold. Therefore, an interval value is more rational to determined as threshold until the number of individual events touches down and levels off at almost zero. The slopes of inter-thresholds are used to detect the signal of change rate. When the average of n (In this case, n is set to 8) consecutive slopes of inter-threshold are closet to zero, the first threshold point in sliding window is flagged as optimal threshold value of an individual teacher's inter-event interval in a week. In Figure 2, the point of 26 minute is possible the optimal threshold.

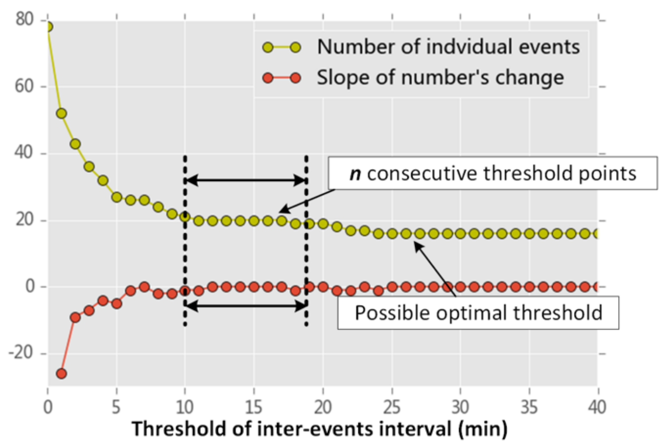

Figure 3. A sliding window which searches an optimal threshold point. Suppose that *n* = 8, the point of 26 minute is possible the optimal threshold

3.2 Creation of Features

We employed event segmentation algorithm in both teachers' and students' action records. The resulting segmented event dataset consists of 10,146 total event rows from 117,324 teachers' authoring action records, and 23, 203 total teaching activity rows from 3,364,533 students' response records. With the respect to trajectory visualization, a process of aggregation is performed in these events for frequency conversion and resampling by a week to generate time series data set. Eight features were distilled from processed dataset:

The total duration of producing event (DE) – Event transformed from teachers' action data which is about producing indicates the fact that they create new media resources and upload files with the authoring platform. The total duration of producing event allows us to know how long would teachers spend on preparing their lessons on the learning platform in a week.

The number of long producing events (LE) – In order to minimize noise in the segmentation, we discretize events (exclusive of single-action events) into three buckets based on quartiles of durations of every events. The producing event with a duration longer than upper quartile is considered as long producing event.

The number of middle producing events (ME) – The producing event with a duration longer than lower quartile and shorter than the upper quartile is considered as middle producing event.

The number of short producing events (SE) – The producing event with a duration shorter than the lower quartile is considered as short producing event.

The number of single-action producing events (SPE) – The events with only one single action are special in this case. A single-action event could be created in the situation where a resource producing last for a long time without any other neighboring action or just a testing action is performed. Therefore, we separate the single-action events into two groups by its action type.

The number of single-action common events (SCE) – The event consists of only one single action which has not explicit relation with producing, such as creating a virtual folder with a default name, are considered as a common event with a single action.

The number of teaching activities (TA) – Teaching activity in this study is about 'consuming' which indicates the evidence that teachers utilize the resources they've uploaded to the learning platform before class. With event segmentation, teaching activity is transformed from students' concurrent response records which include answer submitting, media file uploading and help requesting. The tasks assigned inside e-textbook application by teachers are also considered as the teaching activity even they are mostly finished after class.

The number of engaging days (ED) – The day that teacher is active in authoring platform is considered as an engaging day. However, the single-action common events are omitted when determining whether a teacher is active in a day.

3.3 Contextual Numbers

Self-organizing map is a nonlinearly projecting mapping algorithm which is introduced by Kohonen [7]. The earliest applications were in engineering tasks, later the algorithm has become a generic methodology, which has been applied in clustering, visualization, data organization, characterization, and exploration [6]. Self-organizing map consists of organized nodes that include a N-dimensional weight vector. In regard to the observations $X = \{x_1, x_2, \dots, x_n\}$ in N-dimensional space $x_i \in R^n$, the procedure can be summarized in three processes: competition, cooperation and self-adaptation. The SOM training algorithm can be thought of as a net which is spread to the data cloud. In general, it moves the weight vectors to make them span across the data cloud, so that the neighboring nodes get similar weight vector [7].

Traditionally, most applications of SOM algorithm were organized in a two-dimensional coordinate system (such as [2], [18]). In these applications, after projecting the data to SOM grid, the indexes of nodes as single values are able to create a new contextual order, which can be used to transform each high-dimensional point to a new computational space. The close points are similar in this context, however, this similarity is not interpretable in a single dimensional arrow comparing with classic number space [15].

In this regard, a one-dimensional SOM called *contextual numbers* was introduced by Moosavi [14], this method can be seen as a sequence of ordered numbers pointing to a high-dimensional space, these numbers are ordered according to their similarities within the selected high-dimensional state space or context. In contextual numbers, K nodes will be produced in one-dimension after the mapping of SOM with X, and each node with an attached high-dimensional weight vector represents the original information. Instead of using the values within the nodes, a series new contextual orders were created. It can be summarized in the following steps: 1) Calculate the posterior probability of assigning contextual number; 2) Select the corresponding number when the posterior probability reaches the dominant peak as the node index. The difference between the two-dimensional and the one-dimensional can be reflected in the relation of indices and the weight vector. In a two dimensional grid, the neighborhood similarity expands in two directions. Therefore, there is no direct correlation between the numerical values of indices and the similarity of their weight vectors. But in one dimensional grid, valuable property of contextual numbers is that there is a direct correlation between indices [14]. As in the most two-dimensional cases, the final index of trained SOM will not be used directly as a numerical value but instead of assigned weight vector, contextual numbers allow us to create a continuous number space converted from a high dimension space, which can fit completely to a univariate space [15]. In terms of usage time series analysis in this study, we can have a univariate usage time series for each teacher along the week by conversion of contextual numbers.

It should be noted that the index we mapped to each node is not the classic numbers. The value of these indices are not means the performance grades, but the similarity of two or more nodes. If two index have close values (e.g. node number 1 and node number 2 in SOM network. Numbering is arbitrary, but we usually start from upper-left corner and go row by row) they are similar in this context [15].

3.4 The second staged clustering

With the indices (contextual numbers), hierarchical clustering is performed in this part. One advantage of hierarchical clustering algorithms is that it can help with the interpretation of the results by creating meaningful taxonomies. On account of these numbers implicate contextual information which is difficult to interpret, a common two-staged clustering is employed to combine most similar indexes, as what the previous applications did to the nodes of two-dimensional SOM grid (such as [22,16]). Then a typology from clustering results is developed, which is also proven to make it more accessible when stockholders are involved in exploration of data using visual inspection [5].

In order to get good performance of clustering, first we employ the k-means and the intrinsic metrics—within-cluster Sum of Square for Error (SSE) to compare the performance of different number of clusters. Based on the within-cluster SSE, the elbow method is used to estimate the optimal number of clusters k for a given task. In this study, the elbow is located at k = 5, thus we choose it as the number of clustering. Finally, we perform hierarchy clustering on the contextual numbers.

4. RESULT

This section presents the two stages of our research: in the first part the high dimensional observations from the processed time series data are converted to corresponding contextual numbers, a series of continuous indices and a specific typology which is built for interpretation; in the second part, we apply this to produce visualizations on teacher ICT use trajectory.

4.1 Usage Typology

Firstly, a SOM network is trained on a single dimension network with the eight-dimensions usage data, and the range of indexes is set from 0 to 29. Therefore, each index node has two neighbors except the first and the last. In this regard, we apply the second staged clustering to discretize the contextual number indexes into groups for interpretation, and it is determined that there are five groups to be discovered in our study. The details of the groups are shown in Table 1.

As can be seen in Table 1, Group A characterizes the *Limited use* pattern. Teachers in this group have spent very few time on using the authoring platform. Few product indicates that they never upload media resources; Meanwhile, they organize a few activities once a week, which illustrates the technology is seldom used in their classes; The usage of this group usually is performed at the beginning or the end of semesters.

Group B characterizes the *Early use* pattern. The teachers in this group organize even fewer activities than the teachers in Group A. But they have at least a middle or a short producing event a week, which means some resources were produced to prepare for the lesson., they try to use the platform to prepare lessons. We find out usage of that this group is the mainstream during the first three semesters.

Group C characterizes the *Consuming use* pattern. Teachers in this group begin to use the learning platform more frequently than Group A and Group B. They are very willing to implement this application to organize teaching activities and usually have plenty of responses on the e-textbook, but they only produce at most once a week. We can also find that they have highest single-action common actions than teachers who are in other groups, since they tend to consume the resources rather than produce.

Group D characterizes the *Moderate use* pattern. The teachers in this Group begin to frequently produce resources on the platform, many of them would use the learning platform three out of five working days for every week. Compared to those three groups we mentioned before, teachers in this group are actually using this technology to plan lessons with the resources which are built by themselves. As they are producing frequently, we find that they have highest mid-events. But compared to teachers in Group C, they have slightly less activities which means they are not relying on the e-textbook to teach in classes like teachers in Group C do.

Group E characterizes the *Intensive use* pattern. The teachers in this Group usually heavily produce resources during a long time, they produce many resources on the platform. Among the five working days each week, they almost produce everyday, they also organized numerous activities that means they are actually use the application a lot in class.

Therefore, we can build some meaningful names and stories for every group and create fictitious typology labels to the contextual number indexes, in order to provide an easy way to understand the contextual meaning of indexes. As shown in Table 2, we summarize each group, giving the key characteristics and the indexes belong to.

Table 1. Grouping results showing the mean value for each feature and cluster

	Group				
	A	B	C	D	E
Name	Limited use	Early use	Consuming use	Moderate use	Intensive use
Index	0~5	6~14	15~19	20~25	26~29
DE	0.258	34.161	35.389	78.920	257.665
LE	0.000	0.285	0.288	0.522	2.156
ME	0.000	0.692	0.742	2.597	2.012
SE	0.029	0.371	1.000	0.827	0.514
SPE	0.206	0.432	0.327	0.931	0.452
SCE	0.531	0.532	2.336	1.743	2.218
TA	6.396	2.883	21.107	8.560	32.863
ED	0.025	1.065	1.408	2.866	4.174

Table 2. The user typology derived from two-stage clustering

Group	Indexes	Name	Typology Label
A	0-5	Limited use	Almost no product
			A few activities once a week
			Centralized in the beginning or end of semesters
B	6-14	Early use	Few teaching activities
			At least a middle/short event a week
			The mainstream of the earlier stage
C	15-19	Consuming use	Plenty of activities
			Producing at most once a week
			More independent actions
D	20-25	Moderate use	Frequently producing
			Highest middle-event rates
			Slightly less activities
E	26-29	Intensive use	Heavily producing during a long time
			Almost producing everyday
			Organizing numerous activities

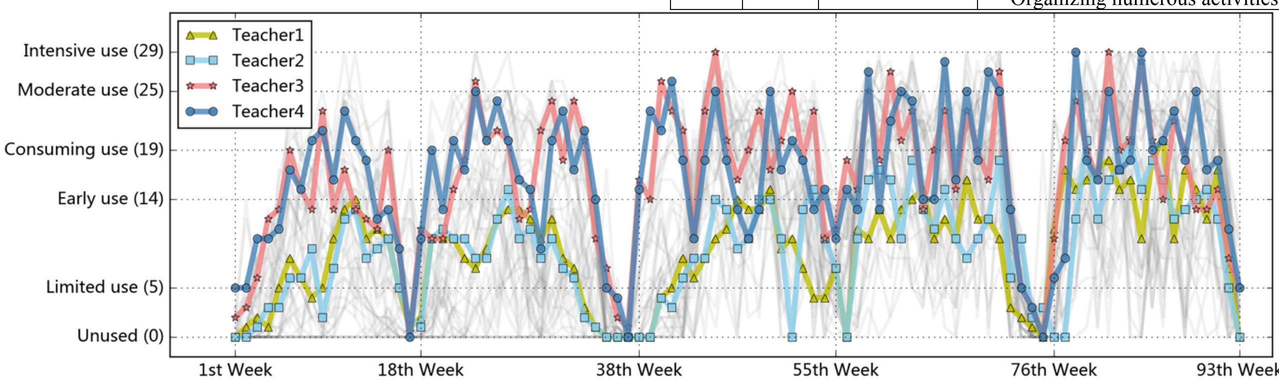

Figure 4. Sample trajectory visualization

4.2 Usage Trajectory

Finally, we can explore visual trajectory with the typology to identify the implicit patterns and hypothesis. This visualization provides the capability to trace states and discovery patterns without reducing the information to simple statistics, it illustrates the teacher usage trajectories which is helpful as teachers and stockholders rarely trace the process of how they use the ICT in teaching.

As shown in Figure 4, Y axis is the index of one dimension SOM and X axis shows the week which is the length of time to be observed in this case. The figure shows the states and trajectories of each teacher over the time. Therefore, similar teacher has similar index number during the time. It allowed us to identify how a teacher uses this technology by comparing the trajectories and pattern of each teacher in relation to the others using the contextual numbers of SOM. If we are familiar to a few teachers' usage, we can consider these teachers as contexts for relative positioning when identifying a new teacher usage, even we don't know the interpretation of the contextual numbers. As shown in Figure 4, we can consider Teacher 3 as a template if we were familiar with the his or her usage or performance, then the usage of Teacher 4 is easy to be identified by comparing their similar trajectories. The result of our statistical analysis on index set shows that the Teacher 3 and Teacher 4 have a lowest Euclidean distance. On the other hand, we can also automatically find similar teachers based on distance calculation between each trajectories.

As the use of an "adopted" technology can vary greatly from one group of teachers to another [9], this figure provide an easy way to partition the teachers in terms of the variations along the two dimensions of contextual index and time of usage. In this case, as shown among the intense user group, Teacher 3 and Teacher 4, the contextual numbers indexes mostly ranged from 10 to 29, which were almost consistently higher than the the indexes of moderate user group, Teacher 1 and Teacher 2, whose usage was mostly labeled as early use or consuming use in the first three semesters. Apparently, Teacher 1 and Teacher 2 adopted this tool for teaching, but did not rely on the tool in the same way that Teacher 3 and Teacher 4 did. However, it is not rational to evaluate the performance of teachers' ICT with the number of index, because the SOM indexes are used as computable numbers to represent the state based on the contexts, but the values of indexes don't follow the concept of natural numbers which can be interpreted as ordered grades. Therefore, the higher index does not always indicate better performance, even though it seems that higher contextual number index is labeled with more intensive use in this case.

This method is also able to indicate potential patterns from trajectories of contextual numbers. As shown in Figure 4, the state of teacher's usage fluctuates visibly over each semester. More specifically, as we can see Teacher 4 in the last semester, at beginning of this semester the number of state stands at a limited usage index. Then, the number shoots up over the next two weeks, peaking at 29, which means a state of intensive use. After that, the contextual number declines rapidly for two weeks, bottoming out at 16 which is labeled as a consuming using index. The next week experiences a very sharp rise, reaching the intensive use area again. According the indexes of usage in the following weeks, a total of 5 peaks can be respectively detected. The peak pattern discovered from trajectory plotting describes a behavior that teacher tends to produce the teaching resources intensively in first one week, then consume them in this week and the following one to two weeks. We apply frequent sequence mining to segmented trajectory data of active teachers to explore this idea, the result shows that the sequences of peak pattern (such as Sequence [Consuming use, Intensive use, Consuming use]) all get highest frequency in the group of their week length.

5. CONCLUSION

This paper introduced a computation procedure for visualizing the trajectories of teacher's ICT usage based on the resource producing process and the experience structure via the implicit patterns within the raw data by event segmentation and contextual numbers. The resulting visualization provides the capability to trace states and discovery patterns without reducing the information to simple statistics, such automated visual characterization might be helpful to the wide and scalable application of teaching analytics to represent teacher's ICT usage. Our future work will be oriented to the *spatiotemporal dynamic* in education, especially the application of ICT, in which the knowledge extraction of web-based education system can be viewed as a formative evaluation technique. In this condition, high-dimensional time series with different features can be replaced by a series of contextual numbers, where this numerical numbers can be embedded in any data driven analysis and prediction [14].

6. ACKNOWLEDGMENTS

We would like thank Liangjun Zhang and colleagues for the tutorial of segmentation algorithm in their practice book.

7. REFERENCES

[1] Dyckhoff, A. L., Zielke, D., Bültmann, M., Chatti, M. A., & Schroeder, U. 2012. Design and implementation of a learning analytics toolkit for teachers. *Educational Technology & Society*, *15*(3), 58-76.

[2] Fournier, H., Kop, R., & Sitlia, H. 2011. The value of learning analytics to networked learning on a personal learning environment. In *Proceedings of the 1st International Conference on Learning Analytics and Knowledge* (pp. 104-109). ACM.

[3] Gašević, D., Dawson, S., & Siemens, G. 2015. Let's not forget: Learning analytics are about learning. *TechTrends*, *59*(1), 64-71.

[4] Gedikli, A., Aksoy, H., and Unal, N. E. 2008. Segmentation algorithm for long time series analysis. *Stochastic Environmental Research and Risk Assessment*, *22*(3), 291-302.

[5] Gibson, D., & de Freitas, S. 2016. Exploratory analysis in learning analytics. *Technology, Knowledge and Learning*, *21*(1), 5-19.

[6] Kaski, S., Kangas, J., & Kohonen, T. 1998. Bibliography of self-organizing map (SOM) papers: 1981–1997. *Neural computing surveys*, *1*(3&4), 1-176.

[7] Kohonen, T. 2013. Essentials of the self-organizing map. *Neural Networks*, *37*, 52-65.

[8] Krüger, A., Merceron, A., & Wolf, B. 2010. A data model to ease analysis and mining of educational data. In *Educational Data Mining 2010*.

[9] Leary, H., Lee, V. R., & Recker, M. 2014. More than just plain old technology adoption: Understanding variations in teachers' use of an online planning tool. *ICLS 2014 Proceedings*, 110.

[10] Levin, T., & Wadmany, R. 2008. Teachers' views on factors affecting effective integration of information technology in the classroom: Developmental scenery. *Journal of Technology and Teacher Education*, *16*(2), 233.

[11] Loui, A. C., & Savakis, A. E. 2000. Automatic image event segmentation and quality screening for albuming applications. In *Multimedia and Expo, 2000. ICME 2000. 2000 IEEE International Conference on* (Vol. 2, pp. 1125-1128). IEEE.

[12] Martinovic, D., & Zhang, Z. 2012. Situating ICT in the teacher education program: Overcoming challenges, fulfilling expectations. *Teaching and Teacher Education, 28*(3), 461-469.

[13] Maull, K. E., Saldivar, M. G., & Sumner, T. 2010. Online curriculum planning behavior of teachers. In *Educational Data Mining 2010*.

[14] Moosavi, V. 2014. Computing With Contextual Numbers. *arXiv preprint arXiv:1408.0889*.

[15] Moosavi, V. 2014. Toward Engendering Contextual Numbers:Self Organizing Maps in Coexistence with Data-Driven Logic. *http://nbviewer.jupyter.org/gist/sevamoo/9543236*.

[16] Ong, S. H., Yeo, N. C., Lee, K. H., Venkatesh, Y. V., & Cao, D. M. 2002. Segmentation of color images using a two-stage self-organizing network. *Image and vision computing*, *20*(4), 279-289.

[17] Prieto, L. P., Sharma, K., Dillenbourg, P., & Jesús, M. 2016. Teaching analytics: towards automatic extraction of orchestration graphs using wearable sensors. In *Proceedings of the Sixth International Conference on Learning Analytics & Knowledge* (pp. 148-157). ACM.

[18] Schreck, T., Bernard, J., Von Landesberger, T., & Kohlhammer, J. 2009. Visual cluster analysis of trajectory data with interactive kohonen maps. *Information Visualization*, *8*(1), 14-29.

[19] Tanes, Z., Arnold, K. E., King, A. S., & Remnet, M. A. 2011. Using Signals for appropriate feedback: Perceptions and practices. *Computers & Education*, *57*(4), 2414-2422.

[20] Vatrapu, R., Reimann, P., Hussain, A., & und Beratung, M. P. F. 2012. Towards teaching analytics: Repertory grids for formative assessment. In *Proc. International Conference of the Learning Sciences (ICLS) 2012*.

[21] Verbert, K., Duval, E., Klerkx, J., Govaerts, S., & Santos, J. L. 2013. Learning analytics dashboard applications. *American Behavioral Scientist*, *57*(10), 1500-1509.

[22] Vijayakumar, C., Damayanti, G., Pant, R., & Sreedhar, C. M. (2007). Segmentation and grading of brain tumors on apparent diffusion coefficient images using self-organizing maps. *Computerized Medical Imaging and Graphics*, *31*(7), 473-484.

[23] Zheng, L., Gong, W., & Gu, X. 2017. Predicting e-textbook adoption based on event segmentation of teachers' usage. In *Proceedings of the Seventh International Learning Analytics & Knowledge Conference* (pp. 560-561). ACM.

[24] Zheng, Q., Liang, G., Quan, Y., Gao, W. and Wang, S. 2015. Analysis method, apparatus and system for user water bath behavioral habits. CN105115164A. 2015(in Chinese).