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Impact of School Closure during COVID-19 Emergency: A Time Series Analysis of Learning Logs

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Abstract: Recent spread of the COVID-19 forces governments around the world to have temporarily closed educational institutions. Although many studies were published to announce the best practice under the school closure, we need to understand the impact of school close on students' learning before that. In this paper, we evaluate the impact of the school closure on our online teaching-learning environment. We use CausalImpact model to infer the impact on our learning analytics system using the learning log stored in the system. The results show that the school closure increased the number of logs on LMS by 163%, but decreased the number of logs on e-book reader by 77%. However, focusing on a particular course, we found that students' learning engagement on online system increased both in LMS and e-book reader. We discussed that it is caused by the following reasons: 1) Changes in major users on our online learning platform, and 2) Limited functions of our e-book reader which was developed for face-to-face learning, not online learning. Further, the results also suggested that CausalImpact model is useful for evaluating the effectiveness of a specific event from learning logs collected by learning analytics systems.

Keywords: Learning Analytics, School Closure, COVID-19, Time-Series Analysis, CausalImpact model, Secondary Education

1. Introduction

UNESCO reported that 90% of students are affected in some way by COVID-19 pandemic (UNESCO, 2020). Most governments around the world have temporarily closed educational institutions in an attempt to contain the spread of the virus. In Japan too, the national government requested temporary school closure for elementary, junior-high, and high school on March 2. For the educational stakeholders, there is an urgent need to respond to this situation as soon as possible. To respond to the needs, many studies were published to announce the best practice under the school closure (Dai & Lin, 2020; Morgan, 2020). However, at the same time, we need to understand the impact of school close on students' learning. Without knowing the current situation, we cannot take measures. To respond these requests, this paper aims to investigate the impact of school close on the online teaching and learning environment at a secondary school in Japan. Our contributions of the paper are follows:

1. As we (our university) have been cooperating with a secondary school even before the disaster, we can directly assess the impact of school closure.
2. A specific time-series model, CausalImpact model was implemented for the first time to evaluate the impact in the educational sector.

The context of our study was a public secondary school in the Kyoto city of Japan. The school had 360 students at junior-high level and 845 students at the high-school level. The junior high students were provided a tablet from the school and high school students have their own tablet or PC. Although the national government requested to close the school on March 2 (Nikkei Asian Review, 2020), the school was actually closed from March 2. During online sessions during emergency period, students access their home internet connection.

In the next section, we will review our online learning platform and time series models used for the analysis.

2. Foundation of current study

2.1 Learning Evidence Analytics Framework (LEAF) and learning logs

We offer an integrated online learning platform called LEAF - Learning Evidence Analytics Framework to a secondary school in Japan (see Figure 1). LEAF consists of three learning support systems - Moodle, BookRoll, and LA view (Flanagan & Ogata, 2018). The first component, is any learning management system (LMS). Moodle is used to host the courses, manage learning resources, and conduct assessments to evaluate students' learning. The second component, BookRoll is an e-book reader, where teachers upload learning materials for students. BookRoll has many advantages compared to just uploading reading materials as a pdf format to Moodle. Teachers can create quizzes and recommendations on the material. Students can write handwritten memos, highlight text, and answer questions on any device which has a browser. Moreover, the interaction logs are stored in the Learning Record Store (LRS) so that teachers can review students' learning activities. LAViEW is the learning analytics dashboard that visualizes the leaner interactions. Teachers can see students' markers, memos, bookmarks, time spent on each page, and other reading behaviors.

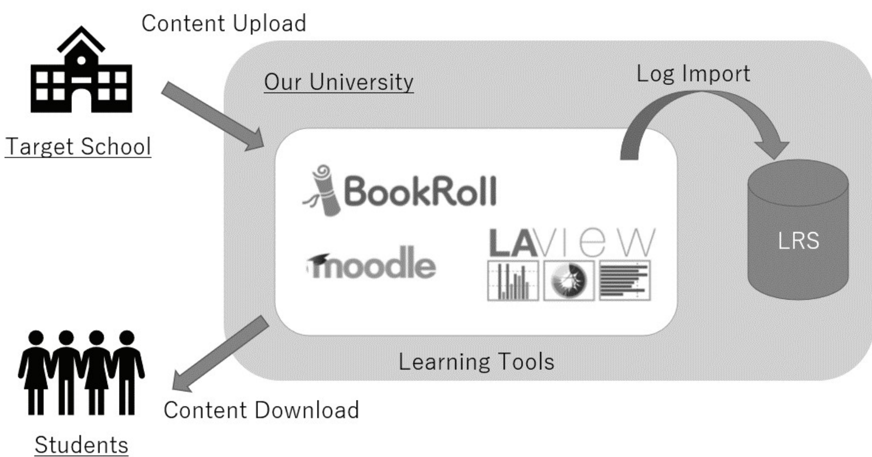

Figure 1. Learning Evidence Analytics Framework (LEAF).

2.2 Time Series Analysis

To evaluate the impact of school closure on our learning platform, we take a time-series analysis approach to the log data stored on the system. We compared two different time periods - before and after the school closure. However, comparing two periods is difficult in time-series data. We cannot apply group-comparison methods such as t-test because time-series data are not independent samples over time. To solve this problem, we examined three time-series analysis models - Interrupted Time-Series, Prophet, and CausalImpact - which are able to deal with the comparison of two time periods.

The first candidate was Interrupted Time Series (ITS) model. ITS model is a study design which evaluates the effectiveness of population-level interventions (Bernal et al., 2017). Mathematically it is the segmented regression model with dummy variables representing the period of the intervention. The advantage of ITS model is its simplicity. As its structure is similar to linear regression models, we can easily interpret the model. However, its prediction power is weak due to the simplicity. Although our purpose is not prediction, it may cause problems in causal inference because of insufficient model flexibilities.

The second candidate was Prophet model developed by Facebook research (Taylor & Letham, 2018). Prophet model is a kind of Generalized Additive Model, which consists of three main components - trend, seasonality, and holidays. The advantages of prophet model are that we do not have to interpolate missing values because it takes time-series analysis as a curve fitting problem and it is proved to have high-accuracy to predict future values. However, our purpose of using statistical model is not to predict future, but evaluate the impact of a specific event. Sometimes it is difficult to infer the effectiveness of an event by Prophet model.

The last candidate was CausalImpact model proposed by (Brodersen et al., 2015). Unlike Prophet model, it is developed to evaluate the impact of a market intervention. It applies Difference-In-Difference (DID) concept to infer the causality from observational data. It offers theoretical evidence of evaluating causal impacts to the model. CausalImpact model evaluates the impact of an intervention *I* by following equations:

$$I = \frac{1}{t-n} \sum_{t'=n+1}^{t} \phi_t^{(\tau)} \quad (1)$$

$$\text{where } \phi_t^{(\tau)} = y_t - \tilde{y}_t^{(\tau)} \quad (2)$$

In the equation (1), we assume that the current time is t and the intervention happened at time n. In equation (2), y is the dependent variable and $\tilde{y}$ is the estimated value by the model. Hence, CausalImpact model compute the impact of the intervention by taking the difference between the predicted value $\tilde{y}_t^{(\tau)}$ and the actual value y_t to make counterfactual inference.

We summarized three models in Table 1. Based on the comparison of the three models, CausalImpact model was selected to be implemented in this study for the following reasons:

1. Causal Impact model specializes in evaluating the impact of an event while other models does not focus on causal inference problem.
2. Both ITS model and CausalImpact model are used for decision making rather than predicting future values, but CausalImpact model can handle with more types of data.

Next section, we will explain the data and our analysis flow of it.

Table 1

Comparison of time-series models

	Interrupted Time Series	Prophet	CausalImpact
Type of Model	Segmented Regression	Generalized Additive Model	State-Space Model
Purpose	Prediction, Decision Making	Prediction	Decision Making
Characteristics	Simplicity	Easy to adjust with domain knowledge	Difference-In-Difference approach

3. Methodology

We conducted two analyses for evaluating the impact of the school closure (see Figure 2). All the log data are collected from Learning Record Store on the LEAF platform.

First, we evaluate the impact on the whole system, looking at the change of accumulated number of logs for each learning tool - Moodle, BookRoll. In this analysis, the logs between April 1, 2019 and April 15, 2020 were considered. We took the number of logs per day as the indicator.

Second, we focused on a specific course log in order to explore the change of their teaching-learning style further. It was an English course in high school for grade one students. The number of teachers and students enrolled in this course were 19 and 280 for each. The reason why we selected the course was that the course was one of the most active courses in Moodle during the school close period and they used both Moodle and BookRoll from the beginning. In this analysis. the logs between April 1, 2019 and March 31, 2020 were considered. We conducted a brief interview to a teacher in the course after analyzing the logs. We took average time spent per student as the indicator of the impact.

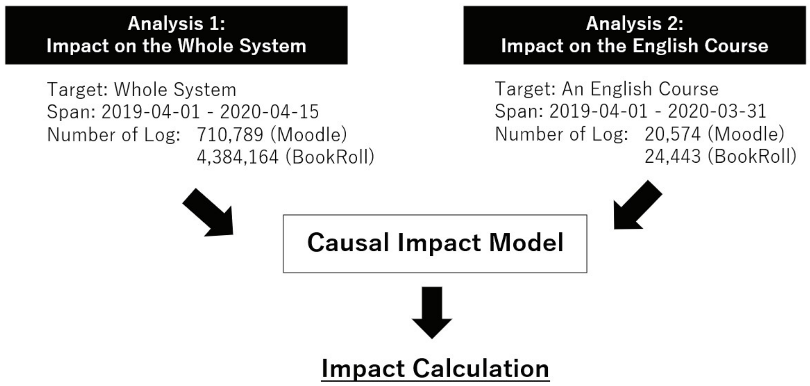

Figure 2. Two analysis flows in this study.

4. Results

4.1 The Impact on the Whole System

We evaluated the impact of school closure to the whole system in terms of number of logs per day. Figure 3 shows the descriptive plot of number of logs in Moodle and BookRoll. Table 2 shows the results of the CausalImpact model fitting. The results showed that the school closure increased the number of logs on Moodle by 163% while decreased the number of logs on BookRoll by 77%. Both confidence intervals (95% CI) were also significant.

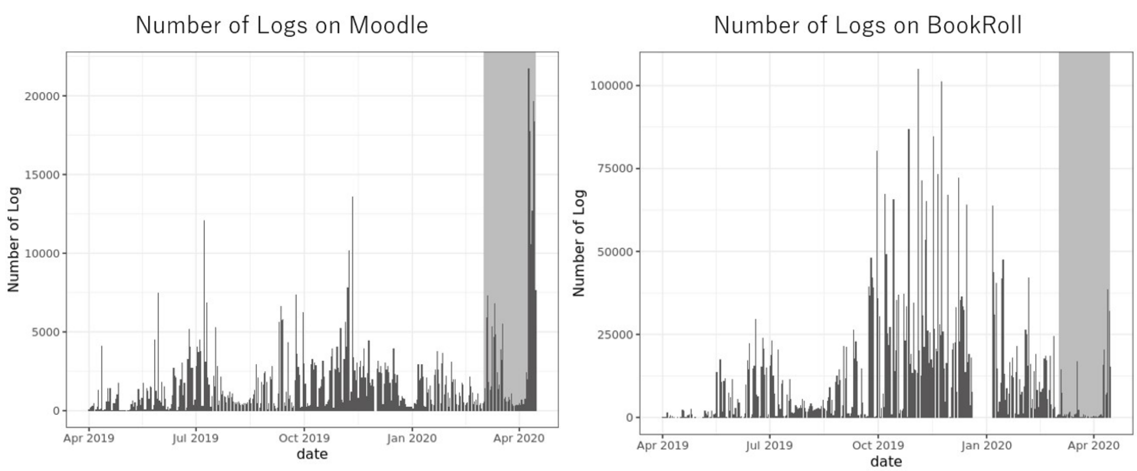

Figure 3. Number of logs on Moodle (left) and BookRoll (right) before and after school close. The gray area represents the school close period.

Table 2

Absolute and Relative Effect of School Closure on the Whole System: Estimated by CausalImpact

	Moodle	BookRoll
Absolute Effect	+2525 logs	-10,069 logs
95 % CI	[1911, 3180]	[-17823, -2678]
Relative Effect	+163 %	-77 %
95% CI	[123, 205]	[-124, -19]

4.2 Impact on the English Course

Next, we evaluated the impact of school closure to the specific course in terms of students' time spent on a day. Figure 4 shows the descriptive plot the amount of time spent in Moodle and BookRoll over the period. We can see that students' learning activities on our online learning platform was more active in the school close period than the normal period. Table 3 shows the results from CausalImpact model. It shows that students' time spent increased in both Moodle and BookRoll (2227% and 875% for each). The confidence intervals (95% CI) are also significant. According to the teachers, the class using our platform increased from once a week to four times a week during the school close period. These results matched to the situation.

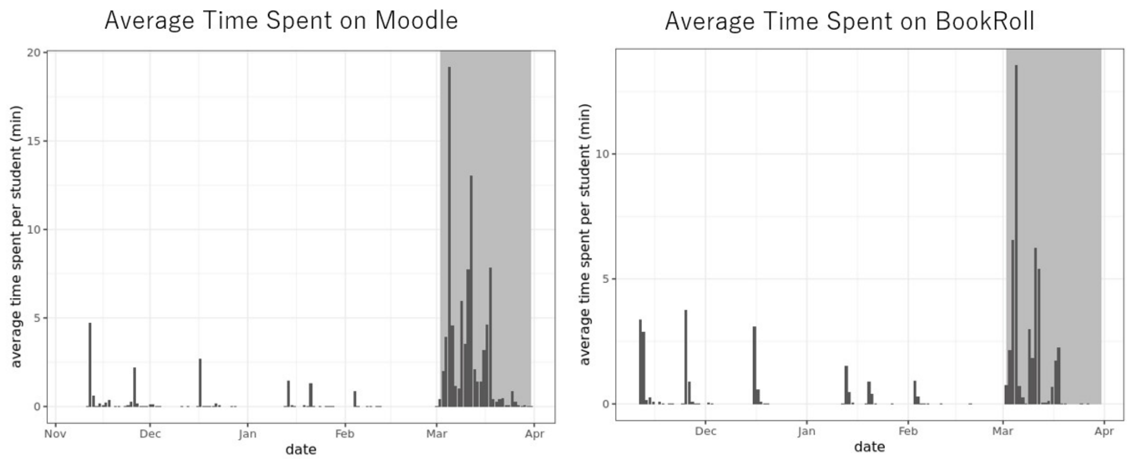

Figure 4. Students' time spent on Moodle (left) and BookRoll (right) before and after the school closure. The gray area represents the school close period.

Table 3

Absolute and Relative Effect of School Closure on the English Course: Estimated by CausalImpact

	Moodle	BookRoll
Absolute Effect (min)	+2.8 min	+1.6 min
95 % CI	[2.5, 3.0]	[1.3, 1.9]
Relative Effect	+2227%	+875%
95% CI	[2021, 2435]	[723, 1036]

The teacher also noted that they started use more function in Moodle such as quizzes and feedback features and upload their original reading materials on BookRoll. Before the school closure, they had used Moodle just as a place to distribute learning materials and they only uploaded the commercially available teaching materials on BookRoll.

5. Discussion

5.1 Cause of the Results

So far, we found that in the school close period, 1) the number of Moodle log increased, while the number of BookRoll log decreased on the whole online learning system, but 2) focusing on a single course, there is a course where time spent on both Moodle and BookRoll had been increased. We expect that the results were caused by the following reasons:

1. Before the school closure, our online learning system was mainly used by junior-high teachers, but after the school closure, the main users were high school teachers. While junior-high teachers were well trained to use BookRoll because they had many training sessions, high school teachers were not.

2. The teachers may think BookRoll was difficult to use BookRoll in online teaching activities. Before the school closure, BookRoll was used in face-to-face learning context. They tend to use videos during the school close period. A previous study (Shatakshi & Nardev, 2020) also pointed out that the most common source of the online classes was "PPTs with Audio", followed by "Videos."

5.2 Novel Application of Analytical Process

Here, we would like to discuss about the applicability of our analysis process as well. CausalImpact model has been used mainly in engineering field e.g. the impact of the cyber policy activation on cyber-attacks (Kumar, Benigni, & Carley, 2016) or the implementation of product modularity on Bus manufacturing (Piran, Lacerda, & Camargo, et al., 2017). To the best of our knowledge, this is the first case of applying CausalImpact model in learning analytics field. Time-series analysis with causal inference theory will be important in learning analytics field. We plan to implement automated intervention evaluation module from learning logs in LEAF platform. It will be useful for teachers who want to review their teaching.

6. Conclusion

In this paper, we presented a process of evaluating the impact of the school closure on the online learning system. We used the CausalImpact model to analyze students' learning logs. The results suggested that the teaching-learning style had changed before and after the school closure drastically and the CausalImpact model is useful for evaluating the effectiveness of some events from learning logs collected by learning analytics systems. Moreover, time-series analysis with causal inference theory will be important in the next learning analytics researches.

Acknowledgements

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