Online Learning Behavior, Peer Effect, and Education

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Abstract

Sociologists and economists are interested in examining the relationship between the characteristics and peer effects of students and their learning outcomes, which generate thousands of literature among the past half centry. Additionally, with the widespread adoption of the online learning platforms, more and more behavior data is collected by the platform, including the learning behavior such as the clicking, speed-up or replay, and posts on the forum. Although data collection raises in this big data era, the behavior data doesn't stimulate many research involved, and few attentions are received in the relationship between the learning behavior and the outcomes. What is the impact of different online time distribution and different learning patterns? Does the friend share a similar online learning behavior or students with the similar online learning behavior are easier to get familiar with?

In this research project, we propose a behavior-driven method that provides us to dive into the new era. The contribution of this research is threefold. First, we present a novel research direction for student's academic outcomes by leveraging the student's online behavior data. We propose several activities as a possible metric to compare the similarity between leaners and cluster learners based on the similarity to confirm whether and how learner behaviors affect their learning outcome.

Second, we empirically analyze the actual student behavior in the online education platform to explore the correlation and the causality for their academic outcome. We examine the collected data from NTU COOL, an online platform providing professors and students at National Taiwan University to hold courses and learn online. Not only to utilize the online website data, but we also plan to collect the student's friendship network to represent the network dynamics and study whether the learning behavior is relative to the friendship or whether students tend to have friends with similar learning behavior.

Third, we nominate learning suggestions for both learners and instructors. By observing learners' online learning behavior, we can detect possible learning problems and help learners better attend the course timely. Moreover, this research can be extended to the different age groups to help schools improve their education policies and teaching plans.

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Long-term Impact

This research project aims to provide a critical theoretical and empirical analysis of online learning behavior, which receives relatively sparse attention from the researchers. Regarding the academic contribution, first, we pave the way to associate the data era with classical social network research. Several types of research are conducted to investigate the study outcomes and the network effects on education. Nevertheless, due to the difficulty of data collection in the past, economists tended to emphasizes the characteristics of learners (Antoni Calvo-Armengol (2009); Lin (2010); Sacerdote (2011)) and no empirical evidence unveiled the mystery behind the learning behaviors. As the broad adoption of online technologies in recent years, especially the large-scale epidemics accelerates the acceptance of online education, millions of learners study different subjects online and leave tons of online learning behavior marks. The research's contribution is paramount to both economics and educational science, since we leverage the direct behavior data from students to track and document the impact of different behaviors. Such a multi-disciplined analysis across the economics, educational science, and computer science in the framework of network effects is currently inexistent, and our methodology may elucidate a new research direction.

Second, we provide a methodological contribution to the future analysis. It is widely believed that longer studying time and different learning habits impact academic achievement (Kember et al. (1996); Jin and W (2015); Simon Calmar Andersen and Nandrup (2016)). Economists and sociologists agree that people do not live isolated, and peer interactions significantly influence students (Christoph Stadtfel et al. (2018)). We use the stochastic actor-based model and the spatial autoregressive (SAR) model for social interaction to study the network dynamics and network effects of learning behaviors. We hope the methodology will encourage researchers to explore how different aspects (e.g., different age groups, cultures, social perception, or the degree of importance of study) shape diffusion.

In regard to the policy contribution, education is an essential concern of children, parents, schools, and countries. As we discover more and more pieces of knowledge, we have no choice but to be forced to learn more and more. This seems to imply that probing a more effective and efficient learning method will be indispensable. By analyzing learning behavior, teachers and students may gain insights into the role of learning behavior and integrate these insights into their teaching and studying. In addition, considering the network effects and dynamics allows us to better understand how socialeconomics networks are involved in our daily life. The potentials and observations reported here help to clarify socioeconomic network power, which is worthy of further investigation and extension to other fields.

Objectives

This research contains the following objectives:

1. Propose a theoretical model that captures the similarity of behaviors for the online education platforms as a metric to cluster students.
2. Explore the relationship and effects between the characteristics and the behaviors and understand whether students with the similar characteristics result in the similar behaviors.
3. Explore whether the friendship network results in similar behavior and vice versa. For example, do the night type students tend to have a friend with the same behavior, or do late-submission type students affects the early-submission type.
4. Construct an empirical approach based on the behavior data and explore the relationship between behavior and academic outcomes.
5. Provide a strategic guide based on the behavior data for learning behavior and a study plan for students and instructors. For example, teammate searching and team allocation.

1 Introduction

Sociologists and economists agree that individual agents interact in huge networks, and the behavior of which is affected by the network externalities (Granovetter (1985)), structure(Burt (1992)), and their peers. Peer effects are commonly observed in the education (Antoni Calvo-Armengol (2009); Lin (2010); Sacerdote (2011) and Gaviria and Raphael (2001)), management (Ramana Nanda (2010)), health issues (Chih-Sheng Hsieh (2018)), and policy decision (Calvó-Armengol and Jackson (2004) and Calvó-Armengoi and Zenou (2004)) in both theoretical and empirical studies. All in all, these works of literature to date seem to confirm the existence and impact of social network effects.

Moreover, with the rapid development, widespread and considerable adoption of online technologies, millions and millions of individuals immensely use online social networking (OSN) sites such as Facebook (Julia Brailovskaia and Margraf (2020)), Twitter, and Instagram. OSNs attract numerous users by allowing them to maintain connections with others and present themselves in the virtual communities (Julia Brailovskaia and Margraf (2020)). A great number of usages results in appreciable data collections by platforms for not only users' personal information (Annie Liang (2022) and Tirole (2021)) but users' online behavior; the websites and applications record users' online time, click behaviors, usage frequency, and posts and comments in the forum. Such online behavior extraction is hugely adopted in recommender systems (Felfernig et al. (2021)), prediction by machine learning (ML) methods (Wu et al. (2020) and Richardson et al. (2007)). The applications are not limited to the business field, Kumar et al. (2019) use actions and timestamps taken by the anonymized users on a popular MOOC platform[1] and construct a dynamic network to predict when a student will drop out from a course.

Not only do computer scientists and business companies notice the development of OSNs and online behavior data, but teachers and educational scholars also attempt to delve into them. Albert C.M. Yang and Ogata (2022) cluster students in three behavioral patterns and find that students who frequently take online assessments after class tend to achieve a higher examination score than those who did not. Rosalina Rebucas Estacio (2017) attempt to extract and visualize students' learning behavior from action logs recorded by Moodle[2], a free and open-source learning management system. These kinds of literature leverage online behavior data to perform the purpose.

Tons of online behavior data is collected nowadays; however, they seem to receive a little attention from economists, although data collection, data analysis, and ML methods are common and trendy in the field of Computer Science (CS). We, economists, have cared about whether and how the characteristics result in the economic outcome (Donnellan M. B. and K. (2009)) or how personal characteristics affect individual behavior for several decades. For example, Hartog et al. (2002) investigated three datasets and found that civil servants are more risk-averse than private-sector employees, and women are more risk averse than men. In this big data era, online platform services are embedded in daily life. It is worthwhile to link and explore the relationship between the behavior, the peer effects, and the economic outcome, especially in education. We want to understand how different behaviors lead to different learning outcomes. Do students who tend to watch course videos late at night achieve a higher grade? What is the impact of different online time distribution and different learning patterns? Does the friend share a similar online learning behavior or students with the similar online learning behavior are easier to get familiar with? Will students who procrastinate in working and submitting the assignments have a significant lower grade? Do students tend to speed up the course videos have a higher grade? That's what we want to scrutinize.

The first objective of this research is to perform a theoretical structure to cluster students via their online learning behavior and then conduct an exhaustive and detailed empirical analysis to examine it. Classical methods include K-means clustering (MacQueen (1967) and Shi et al. (2010)), hierachical clustering (Defays (1977)), and modularity-based methods (Newman (2006) and Delling D et al. (2008)). In addition, tens of algorithms are applied in this field, such as the Louvain algorithm (Blondel Vincent D and Etienne (2008)). In this context, how to describe online learning behavior as a metric to determine the similarity between two users is the first priority.

The second objective of the research is to illuminate the darkness between peer effects and behaviors. The numerous literature abounds with theoretical model and empirical results on revealing the impact of peer effects but rarely devote any time to a systematic study of the influence of peer effects on online learning behaviors. Moreover, the influence of dynamic network evolution on online learning behavior is also essential. Christoph Stadtfel et al. (2018) investigate a cohort of 226 engineering students starting their undergraduate studies and use statistical models for dynamic network data to investigate the cohort's social network formation processes. They find that friendship ties crucially affect academic success and suggest the university promotes

[1] https://www.mooc.org
[2] https://moodle.org

the development of positive relationships. Students strike up a friendship through time, and we want to examine how network dynamics and friendship ties affect the learning behavior, or conversely, how the learning behavior affects network dynamics and friendship.

The third objective of the research is to provide learning suggestions to students and instructors. With a thorough study of online learning behavior and the corresponding insights, we may offer a better study plan to both students and instructors. For example, assume that the procrastination may lead to a terrible grade, the instructor can find students in the procrastination and help them earlier. Online learning behavior may also reveal students' preferences. Students who tend to finish assignments early may prefer joining a team with a similar type of teammates. We want to figure out the secret behind the behavior.

With these questions in mind, the research results may help raise the economists' and educational scolars' attention for exploring the possibility of learning behavior, and also help students and teachers better acknowledge the role of learning behavior in studying.

2 Research Methodology

In this section, we organize the current methods to capture the behavior statistics, derive the similarity, detect communities, represent the network dynamics, and evaluate the influence of behavior.

2.1 Behavior Extraction

Online platforms record several different actions from users, and it is crucial to extract behaviors from data. For example, NTU COOL[3] documents total activity time, activity (page views) by date, the number of communications, submission time, and assignment grade. If the instructor has uploaded course videos to NTU COOL, the videos' completion rate, activity (fast forward, rewind, and pause clicks), playing speed, and the number of video comments is also recorded.

Not only the web activities but learners in-time motions are also also worthy of track and examination. In the experimental economics, eye-tracking technology has been used to design, implement, and analyze an experiment using this technology to study economic theory (Lahey and Oxley (2016)).

These activities uncover the students' online learning behaviors and learning preferences. Further research is needed to colloborate and complete the findings in this area.

2.2 Similarity

Robert L. Peach and Barahona (2019) use the time-stamped series of completion times for tasks and the time-stamped data of page-clicks from each leaner in the dataset as a metric and adopt a dynamic time wrapping (DTW) kernel (Berndt and Clifford (1994) and Bagheri et al. (2016)) to calculate a pairwise similarity between time-series of learner actions, construct the leaner similarity graph, and then apply the community detection to cluster learners according to their similar time-series behaviors.

Given two leaners i and j in the set of N leaners $\mathcal{D} = \{1, \cdots, N\}$ and the time-series of actions S_i, S_j, where $S_i = [s_{i1}\, s_{i2} \cdots s_{in}]^T$ and $S_j = [s_{j1}\, s_{j2} \cdots s_{jm}]^T$; that is, the compared time-series can be in different length. Common approaches for sequence analysis exploit L_p-norms between S_i and S_j for its convenience and fast computation; however, such an approach is a one-to-one mapping, which often neglects and misaligns sequential patterns. Dynamic time wrapping can overcome this problem and have advantages over L_p-norms in its elastic and robust matching. The DTW cost of two time-series S_i, S_j at (p, q) is

$$c(p,q) = ||s_{ip} - s_{jq}||^2 + \min\{c(p-1,q), c(p-1,q-1), c(p,q-1)\},$$

and the DTW similarity is the longest path between S_i, S_j, i.e., $\delta(S_i, S_j) = c(n, m)$.

Moreover, the DTW similarity kernel is defined as

$$k\left(S_i, S_j\right) = \exp\left\{\frac{-\delta(S_i, S_j)}{\sigma^2}\right\}.$$

We use the DTW similarity kernel to represent the similarity (or distance) between learner i, j. Therefore, the similarity matrix Y is a $N \times N$ matrix where the value of element y_{ij} is $k(S_i, S_j)$, and Y can be treated as a weighted and fully connected adjacency matrix.

[3] https://cool.ntu.edu.tw

The calculation of DTW similarity may become computational consuming with the growing number of leaner or longer time series. Therefore, dimensionality reduction methods are imperative and can be implemented to accelerate the computation. Several methods are proposed and used in ML applicationd, such as principal component analysis (PCA), singular value decomposition (SVD), or relaxed minimum spanning tree (RMST). As we do not need to connect all nodes (learners) in the graph, we can use the RMST algorithm to prune the similarity matrix (see Beguerisse-Díaz et al. (2013)).

Given the similarity matrix Y, we define the *dissimilarity* matrix Z with $z_{ij} = 1 - y_{ij}$. Next, we find the maximal weight in Z along the maximum spanning tree path as

$$b_{ij} = \max\left\{z_{ik}, z_{kh}, \cdots, z_{cj}\right\}.$$

If b_{ij} is much smaller than z_{ij}, we discard the direct link between i, j; if z_{ij} and b_{ij} are comparable, we leave the link between i, j if

$$b_{ij} + \gamma(d_i + d_j) > z_{ij},$$

where $d_i = \min_k z_{ik}$ and γ is a parameter. Such RMST method merges local and global impact of the data to sparsify the network. Meanwhile, pruning the network help community detection methods speed up and save computation time.

2.3 Clustering

Community detection methods allow us to detect groups with similar properties and extract groups for various reasons and interests. Tens of methods can be used to separate the nodes of a graph into subgraphs, including K-means clustering, hierarchical clustering, modularity-based methods, and Markov stability and vector partitioning (Liu and Barahona (2018)). This research can use either K-means clustering and Markov stability or vector partitioning methods. The former can specify the number of target clusters, and the latter is a generalized method that uses the diffusion of a Markov process on the graph to unveil the subgraph at all scales. We can shift between two methods depending on the purpose. More specifically, if we merely need two subcommunities to separate learners, we can adopt K-means clustering.

We aim at partitioning students in different group based on their extracted behavior properly and revealing the interactions in the group members. A general iterative cluster approach is to minimize the distance between each node and the center of group, and update the center iteratively. Given a d-dimensional set of N students properties $\mathcal{X} = \{x_1, \cdots, x_N\}$ and K groups, we define a d-dimensional set of K clusters $\mathcal{C} = \{c_1, \cdots, c_K\}$, the objective function of K-means clustering algorithm optimizes

$$f^{\mathrm{KM}}(\mathcal{X}, \mathcal{C}) = \sum_{i=1}^{N} \min_{j \in \{1, \cdots, K\}} ||x_j - c_j||^2.$$

A membership $0 \leq m_j^{\mathrm{KM}}(c_j|x_i) \leq 1$ defines the proportional of data x_i belonging to the group j with the center c_j, and the weight $w(x_i) > 0$ reflects the influence in updating the new center in the group. In the K-means scenario, it is

$$\begin{aligned} m_j^{\mathrm{KM}}(c_{j^*}|x_i) &= \begin{cases} 1 & \text{if } j^* =_j ||x_i - c_j||^2 \\ 0 & \text{otherwise,} \end{cases} \\ w^{\mathrm{KM}}(x_i) &= 1. \end{aligned}$$

Another common Bayesian approach is the Gaussian expectation-maximization (GEM). It minimizes the objective function of GEM

$$f^{\mathrm{GEM}}(\mathcal{X}, \mathcal{C}) = -\sum_{i=1}^{N} \log\left(\sum_{j=1}^{k} p(x_i|c_j)p(c_j)\right),$$

where $p(x_1|c_j)$ is the probability of x_i conditional on that it's generated by the Gaussian distribution with center c_j, and $p(c_j)$ is the prior of c_j. The membership and the weight in the GEM scenario is

$$\begin{aligned} m_j^{\mathrm{GEM}}(c_j|x_i) &= \frac{p(x_i|c_j)p(c_j)}{p(x_i)} \\ w^{\mathrm{GEM}} &= 1. \end{aligned}$$

Lastly, the steps of iterative algorithm is:

1. Initialize the center $\mathcal{C}$.
2. For each x_i, compute its membetship $m_j(c_j|x_i)$ and weight $w(x_i)$.
3. Recompute each center c_j after assigning x_i to one group.
4. Repeat the step 2 and 3 until convergence.

The time complexity of clustering algorithms above is $\mathcal{O}(nkd)$.

2.4 Dynamic Evolution

Network dynamics can be studied by the spatial dynamic panel data (SDPD) model (Lung-fei and Yu (2010)) and the stochastic actor-based model (Snijders (1996) and Snijders (2017)). The stochastic actor-based model has been studied in several fields, varying from statistics to psychology and medicine. It can represent numerous influences on network change, allow to estimate parameters expressing such influences, and test corresponding hypotheses. The difficulty of network dynamics results from multi changes in network structure and the individual behavior. Individual behavior is often not only influenced by networks but also imposes influence on networks. Researchers impose several assumptions on the problem and adopt a continuous-time Markov process to ease the problem. It is commonly assumed that the changing system consisting of network and behavior follows a Markov process, and no more than one network variable or behavior variable can change at any moment t.

Given a changing network on n individuals $\mathcal{G}$ [4] and the vector of behavior state of individual i $Z_i = [z_i(1), z_i(2), \cdots, z_i(t)]$, $\lambda_i^{\mathcal{G}}, \lambda_i^Z, f_i^{\mathcal{G}}, f_i^Z$ are rate functions for a Possion process and objective functions of $\mathcal{G}$ and Z. We first present the objective function of individual i for the network and the behavior:

$$f_i^{\mathcal{G}}(g,z) = \sum_j \beta_j^{\mathcal{G}} s_{ij}^{\mathcal{G}}(g,z) \quad \text{and} \quad f_i^Z(g,z) = \sum_j \beta_j^Z s_{ij}^Z(g,z),$$

where $s_{ij}^{\mathcal{G}}(g,z)$ and $s_{ij}^Z(g,z)$ are utility functions depending on the behavior of the focal individual i and the network, which also provides the micro-foundation.

Since the chances for change are for either the network or the behavior of the individual, given the individual i has an opportunity for change in behavior, the current state value $z_i(t) = s^0$, the option for the next possible state $z^0 - 1, z^0, z^0 + 1$, the probability of state transition is

$$p_i^Z(\beta, g, z^0, z) = \begin{cases} \frac{\exp\{f_i^Z(\beta,g,z^0,z)\}}{\sum_{\delta=-1}^{1}\exp\{f_i^Z(\beta,g,z^0,z^0+\delta)\}} & \text{if } z = z^0+\delta,\ \delta\in\{-1,0,1\} \\ 0 & \text{otherwise.} \end{cases}$$

We can use the average similarity effect

$$s_i^Z(g,z) = g_{i+}^{-1}\Big|_{t-1} \sum_j g_{ij}\Big|_{t-1}\left(\text{sim}_{ij}^Z - \overline{\text{sim}}^Z\right)\Big|_t$$

to capture the effect of network incluence, where

$$\text{sim}_{ij}^Z = \frac{1-|z_i - z_j|}{\max_{ij}|z_i - z_j|}$$

and $\overline{\text{sim}}^Z$ is the mean of similarity. In addition, the homophily from certain behavior can be captured by the similarity effect

$$s_i^{\mathcal{G}}(g,z) = \sum_j g_{ij}\Big|_t \left(\text{sim}_{ij}^Z - \overline{\text{sim}}^Z\right)\Big|_{t-1}.$$

Furthermore, we can use the Generalized Method of Moments (Viviana Amati and Snijders (2015)) and Bayesian Markov chan Monte Carlo approach (Handcock et al. (2007)) to estimate parameters for network and behavior $\beta^{\mathcal{G}}, \beta^Z$.

[4] A network $\mathcal{G}$ is a $n \times n$ adjacency matrix.

2.5 Social Interactions Model

Now that we can cluster learners from their behavior similarity, and it is natural to examine what behavior is more effective and efficienct for learners. The traditional model for studying peer effects is the linear-in-linear model (maskin 1993). However, the linear-in-linear model suffers from the reflection problem, preventing researchers from identifying endogenous and contextual effects. Fortunately, the spatial autoregressive (SAR) model can overcome the reflection problem. The network interaction model with the endogenous and contextual peer effects and the group effects is specified as

$$y_{ig} = \lambda \sum_{j=1}^{m_g} \overline{w}_{ijg} y_{jg} + \beta_1 x_{ig} + \beta_2 \sum_{j=1}^{m_g} \overline{w}_{ijg} x_{jg} + \alpha_g + \varepsilon_{ig}, \quad g \in \{1, \cdots, n_{\mathcal{G}}\},$$

where y_{ig} is the outcome of interest for the individual i within the group g, x_{ig} is the independent variable for the individual i within the group g, and $\overline{w}_{ijg} = \frac{w_{ijg}}{\sum_j w_{ijg}}$, $w_{ijg} = 1$ if individual j is i's friend. $\lambda, \beta_1, \beta_2$ and α reflect the endogeneity, the own effect, contextual (peer) effect, and the fixed group effect.

To probe more deeply the influence of online learning behavior, we emphasize on the estimation of group effect α to evaluate different behaviors.

3 Data Collection

We collaborate with the Center for Teaching and Learning Development Digital Learning Center at National Taiwan University(NTU). They offer an online teaching and learning platform, NTU COOL[5], to serve faculty members and students at the university to use digital technologies and media materials in the course. NTU COOL team collect several user activities to do the research, including total activity time, activity (page views) by date, the number of communications, submission time, and assignment grades. If the instructor has uploaded course videos to NTU COOL, the videos' completion rate, activity (fast forward, rewind, and pause clicks), playing speed, and the number of comments on the video.

Furthermore, as the research is relative to personal information, to protect the rights and welfare of human research subjects recruited to participate in research activities, our research will be verified by the institutional review board (IRB) from the Center for Taiwan Academic Research Ethicals.

In addition to the online learning behavior, we are also interested in the network dynamics, behavior diffusions, and peer effects. Following the Christoph Stadtfel et al. (2018), we plan to track a cohort of freshmen and document various individual and socioeconomic background variable to conduct the empirical setting to examine that with the growing links between learners and the emergence of social networks, whether learners' online learning behaviors are affected by peers, and whether learners' behaviors influence the network emergence and formation.

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[5] https://cool.ntu.edu.tw

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