A Framework for Interactive Exploratory Learning Analytics

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Abstract. Many analytic tools have been developed to discover knowledge from student data. However, the knowledge discovery process requires advanced analytical modelling skills, making it the province of data scientists. This impedes the ability of educational leaders, professors, and advisors to engage with the knowledge discovery process directly. As a result, it is challenging for analysis to take advantage of domain expertise, making its outcome often neither interesting nor useful. Usually the outcome produced from such analytic tools is static, preventing domain experts from exploring different hypotheses by changing data models or predictive models inside the tool. We have developed a framework for interactive and exploratory learning analytics which begins to address these challenges. We engaged in data exploration and hypotheses generation with our university domain experts by conducting two focus groups. We used the findings of these focus groups to validate our framework, arguing that it enables domain experts to explore the data, analysis and interpretation of student data to discover useful and interesting knowledge.

Keywords: Learning analytics · Exploratory data analytics
Educational data mining · Learning analytics framework

1 Introduction

One of the common challenges faced by researchers applying data-driven methods to educational settings is the scale of student data both in size and diversity of data sources. Digital technology in educational environments facilitates recording interactions between entities such as learners, faculty, and course materials, all of which produce significant volumes of heterogeneous data. Learning management systems can also generate logs from the online activities of students in the class. As in all big data projects, this increase in the scale of student data typically creates a corresponding increase in the difficulty in extracting knowledge.

While there are a wide variety of solutions used by data scientists to make sense of data at this scale, most fall within a process known as knowledge discovery in the data mining domain. This process includes data cleaning, feature extraction, data patterns identification, and evaluation as steps to discover interesting knowledge from massive

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amounts of raw data. Similar to the knowledge discovery process in data mining, the learning analytics community has adopted the same steps for analytics processes in learning environments. For example, Chatti et al. [1] describes the process as an iterative cycle of (1) data collection and pre-processing, (2) analytics and action, and (3) post-processing.

However, the knowledge discovery process requires substantial data science skills, making it difficult for domain experts and educational leaders to engage with the discovery process directly. As a result, the outcome of the process is either not interesting (in that it is a piece of knowledge of which domain experts are already aware), or it is not useful (it is not actionable, in that experts cannot design an intervention that leverages it). Since most faculty are not engaged with the knowledge discovery process, we cannot expect to have educational research integrated with the computational aspects of learning analytics [2].

We engaged in data exploration and hypotheses generation with our university domain experts and conducted two focus groups. Findings of both focus groups validated the need for an interactive exploratory learning analytics framework that enables domain experts to explore the data, analysis and interpretation of student data to discover useful and interesting knowledge.

Several frameworks for learning analytics were built around the knowledge discovery process, each focusing on a different aspect or dimension of the field. Chatti et al. [1] proposes a reference model capturing four important dimensions: What (i.e. data and environments), Why (i.e. objectives), How (i.e. techniques), and Who (i.e. stakeholders). Greller and Drachsler [3] extends the framework by including two more dimensions: internal limitations (i.e. competence and acceptance), and external limitations (i.e. conventions and norms). While the previous frameworks view the internal elements of the learning analytics, Gašević et al. [4] proposed a holistic view of the field. Gašević's framework explains how learning analytics can interact with data science, learning theories, and learning and study design.

Our interactive exploratory learning analytics framework emphasizes the exploration of both the content in the student data model and the analytic process. This makes it distinct from, but compatible with, previous frameworks that give insights about the structure, process, and interactions of different elements in the learning environments. While state-of-the-art approaches select the factors for analysis (i.e. the features which make up the input) as a precursor to knowledge discovery, our approach pursues the development of the analytics process within an interactive framework in which the data model and the analytic model can be inspected and modified at any point in the knowledge discovery process. Specifically, our approach differs from the previous frameworks in:

- Iterative interaction between domain experts and the data mining process.
- Changing the role of the domain expert from the receiver of knowledge discovered by the data scientists to an active collaborator during the knowledge discovery process.
- Directing the exploratory data analysis towards generating more interesting and useful outcomes.

– Speeding up the lifecycle of analytics and policy-change by involving domain experts in the analytics process.

We present a review of learning analytics research and knowledge discovery in Sect. 2. In Sect. 3, we introduce the interactive exploratory learning analytics framework, and present the results of our focus groups. We discuss current research trends viewed from our proposed framework and directions for future work in Sect. 4 as a conclusion.

2 Background

In this section, we review the literature in two domains: learning analytics and knowledge discovery. First, we explore research in learning communities, and focus on proposed analytical methods in the learning domain. Then, we review research in knowledge discovery that inspired us to create the interactive exploratory learning analytics framework.

2.1 Approaches to Analyzing Student Data

We divide methods for analyzing student data into three approaches: observational, computational, and visual. Observational analysis is the traditional approach: researchers build hypotheses from observations and support a hypothesis using data. Computational analysis searches for patterns in data and lets the data speak for itself. Visual analysis uses human perception to find patterns or limit the search, typically in combination with computational analysis. Visual analysis can also be used to involve students in the analytics process by showing them visualizations of their activity. This can increase motivation and self-reflection for students [5].

In observational analysis researchers start with a specific observation such as the effect of textbook choice on course grades and then try to support this observation with surveys, statistics or data mining tools. For example, Landrum et al. [6] proposes measures for textbook preferences and conducts studies to examine the effect of different textbook preferences on student performance. Bos et al. [7], in another example of observational analysis, observe that online (recorded) lectures can impact student learning. Results of the study show that students participating in both activities including attending lectures and watching online lectures outperform (in exams and assignments) those students who participate only one or no activities. There is, however, no significant difference between students that participate in each activity alone.

Observational analyses rely on expert knowledge to identify what can be observed in the context of learning and how this observation can have potential effects on the learning setting. The observational analysis has the following limitations:

- Observational analysis works best in a deterministic environment. However, when the environment being studied includes human behavior, the observations become dependent on context, a small change in which might substantially affect results.

- Observational analysis requires that each hypothesis be manually constructed. This kind of analysis is limited in its ability to take large amounts of information into account before developing hypotheses due to sheer scale.
- In observational analysis, researchers are primed with the observation. The priming can produce an unintentional bias in approach taken to explore and analyze data. This bias can also limit the search towards only those patterns that are already understandable and observable by the data scientists.

Computational analysis is a response to the limitations of observational analysis. It shifts data mining towards approaches that learn from the data rather than relying on observations of domain experts. In contrast to observational analysis, research in computational analysis focuses on finding patterns in educational settings without having made specific prior hypotheses. This can be useful for obtaining a general view of learners' activity, finding groups (clusters) in data to understand underlying structures or even in identifying irregularities in data.

For example, Ma et al. [8] classified students based on association rules and a score function to identify weak students. Similar approaches in Minaei-Bidgoli and Punch [9], Morris et al. [10], and Bravo and Ortigosa [11], could predict the learning outcome (final grade or course completion) with relatively high accuracy. Romero et al. [12] explored Moodle student activity log data to obtain a general view of student activity. Romero et al. [12] built a complete data mining pipeline for analyzing student activity on Moodle, from data collection and preprocessing to applying a machine learning algorithm and rule generation. They proposed data exploration and visualization tools for better understanding of student data. Later approaches focus more on analytics that generate actionable knowledge rather than emphasizing the common-sense predictors of student success such as GPA and course assignment grades. Course Signals [13–16] is one of the successful learning analytic tools that not only classify and identify students at-risk but also makes interventions to improve student learning based on analyzed data. Based on the Course Signals system, Jayaprakash et al. [17], proposed the Open Academic Analytics Initiative (OAAI) that uses predictive analytical tools to identify students at-risk of course failure. OAAI uses four sources of data to predict if a student is "at-risk". OAAI system uses two intervention tools to improve student learning after it detects a student who is at-risk: sending notification emails and asking the student to participate in learning support systems. Another use of computational analysis is to automatically discover patterns without having prior observation. For instance, Macfadyen and Dawson [18] analyzed Blackboard student interaction data to find features correlated with student final grades to create an "early warning system" for students at-risk. The features include the total number of discussion messages posted, the total number of mail messages sent and the total number of assessments completed.

The most common goal of computational analysis is to find patterns in data which:

- Informs about facts and increases understanding about student data.
- Provides actionable knowledge that can guide further decisions.

Another approach to analyze student data to improve student performance is to visualize the data. Visualizing data can act as a preamble for the computational analysis to facilitate the process or it can be used by itself to increase motivation and self-reflection for the students by showing them the visualizations in a dashboard. We focus on the latter and investigate how presenting students a dashboard can help them reflect the learning and motivate them. Santos et al. [5] and Martinez-Maldonado et al. [19] use this approach to motivate the students.

The success of visual analysis depends on the researcher's preparation and visualization of the data in such a way that it conveys the information succinctly and as comprehensively as possible. A well-designed visual analysis should assist the researcher in addressing the following questions: How does a visualization present a data model that informs the viewer (or the students) of expectations? Is a visualization able to show the trends in the data so that it builds expectations for the viewer?

2.2 Knowledge Discovery

Knowledge discovery in big data projects typically follows four steps to discover knowledge and make sense of massive data sources [20]. These steps, shown in Fig. 1, are in an iterative sequence that starts with preprocessing - cleaning and integrating the data sources. The preprocessing step is followed by data selection and transformation to a representation that contains the necessary features for data mining. The third step in knowledge discovery is to apply the data mining algorithm on the transformed data. In the last step, the results of the data mining algorithm are evaluated and presented.

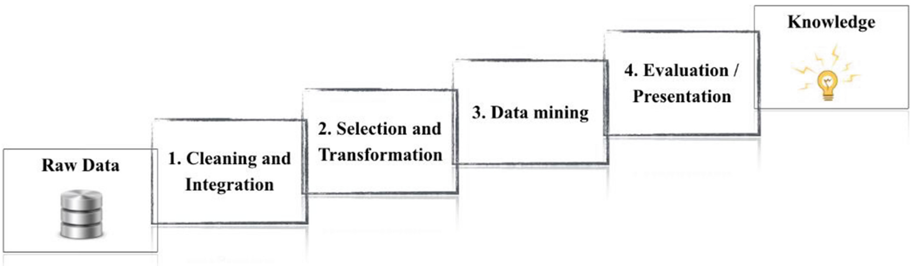

Fig. 1. The process of knowledge discovery adapted from Han et al. [20].

One approach to knowledge discovery in big data, both within education and more broadly, is to detect parts of the data that are interesting. Based on Han et al. [20], interesting patterns are generated in the third step of knowledge discovery process, and evaluated in the last step by a data scientist. Current research in knowledge discovery and data mining has a focus on automatically detect interesting patterns. Geng and Hamilton [21] reviewed techniques for automatically detecting interesting patterns, finding that most of them can be described as objective, subjective, or semantic. Finding automated interestingness measure still remains a challenge, and many such measures have been proposed. McGarry [22] investigated interestingness in knowledge discovery research, and suggested that surprise is the key to find actionable interesting patterns. McGarry [22] describes surprise in terms of unexpectedness, novelty, and actionability. Similarly, but in the domain of association rule mining, Yuejin et al. [23]

defines interestingness as the union of novelty, unexpectedness, surprise, usefulness, actionability, and applicability.

3 Interactive Exploratory Learning Analytics Framework

Analytical approaches in the learning domain generally follow a similar process to the Han's [20] knowledge discovery process. For example, Chatti et al. [1] characterizes the process as a cycle of data collection and preprocessing, analytics and action, and post-processing. In our description of the learning analytics process we use more general terms for naming the four steps of the process: data collection, feature extraction, analytical approach, and evaluation.

Data collection: The learning analytics process starts with collecting data about students. Student data may include students' background information, academic performance, and LMS interactions such as assignment scores, quizzes and forum participations. A recent trend in learning analytics is to incorporate data related to student social networking usage, an area referred to as "social learning analytics" [24–26]. In social learning analytics researchers are investigating aspects of learning in social and informal contexts. The data collection step contains all the necessary preprocessing tasks to collect, integrate and clean the various student data sources.

Feature Extraction: In the feature extraction step collected data is transformed into a student data model that has the necessary features needed for analysis. These features are usually engineered by researchers and often tailored to the analytical algorithm. Student demographic, academic background information, and student performance scores are among the most common features used by researchers.

Analytic Approach: The next step is where an analytical method is used to build visual, statistical, and/or predictive models based on the data model created in the previous step. The analytical method can be from any of the three approaches: observational, computational, and visual.

Evaluation: In the last step of the learning analytics process, data scientists generate potentially interesting patterns from the student data using the analytical approach. The patterns are evaluated using several measures such as accuracy and coverage (recall) over the data set. Evaluation measures are also used by data scientists to assess and validate the overall analytical approach. Based on the evaluations, data scientists decide to refine the process and iterate one more time or to stop and report back the results.

We developed an interactive framework around this process as shown in Fig. 2. This framework has a loop that starts and ends with the domain expert. The domain expert builds a data model based on a challenge, then runs an analytical model to automatically produce potentially interesting patterns (the outcome) that can be used to solve the challenge.

Interactivity is critical feature of the framework shown in Fig. 2. Traditionally a knowledge discovery process such as the process shown in Fig. 1 is carried out by data scientists, with only the finished result shown to other domain experts. The data scientists iteratively perform the knowledge discovery process to obtain potential interesting patterns and by the end of the process present the results to the domain experts.

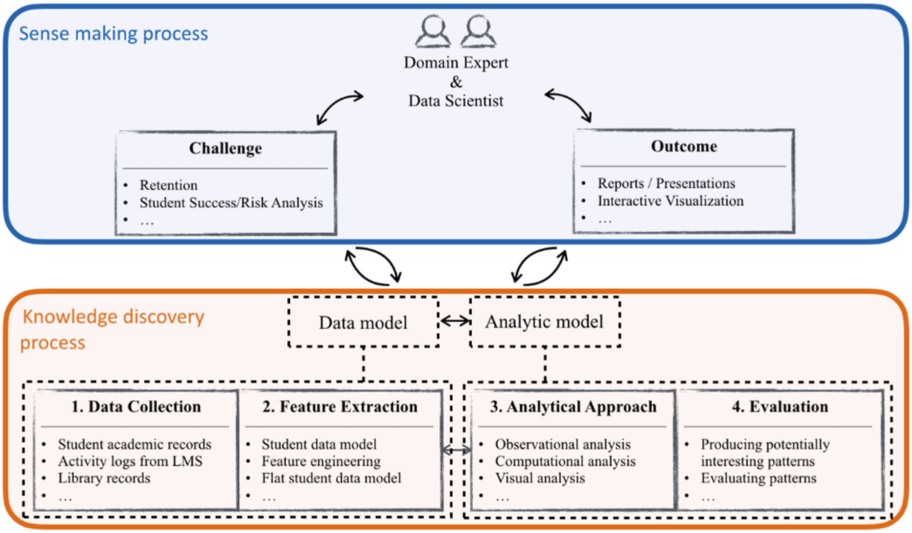

Fig. 2. Interactive exploratory learning analytics framework.

In case the results were not interesting or useful to the experts, the data scientists use the feedback received from the experts to revise and perform the knowledge discovery process again. Technical skill requirements typically prevent domain experts from being "in the loop" and providing feedback during the process of iterative refinement.

The separation of domain expert from the loop limits the discoverability of patterns that are both interesting and useful, as the data scientist may not possess all the knowledge necessary to make those judgements accurately without input from domain experts. Our framework has the domain expert in the loop to define and exploit the knowledge discovery process.

As illustrated in Fig. 2, the interactive exploratory learning analytics framework contains five entities: Domain expert and data scientist, challenge, data model, analytic model, and outcome. Domain experts includes faculties, stakeholders and policymakers of the learning environment. They are actively involved with the learning domain challenges such as retention or identifying students at-risk to improve the learning environment. Challenges are defined by the domain experts in the beginning of the interaction and can be refined during later iterations of interaction. Once the challenge is defined by the domain expert, the analytics process containing the data model and the analytic model can be run to address the challenge. In the next iterations of interaction, the domain expert can explore different options for the data model and the analytic model to see the effects of changes on the outcomes. This exploration is directed towards obtaining more useful and interesting outcomes as the domain expert evaluates them in each iteration and incorporates the background knowledge into the process.

The interactive exploratory learning analytics loop iterates until the analytics process is refined and tailored to the challenge to be able to produce both useful and interesting outcomes. The exploratory feature of the framework allows the domain expert to be part of the analytics process, and the interactivity in the framework makes it possible to achieve useful and interesting outcomes much faster and more efficient than the traditional approach by involving the domain expert into the process.

In addition to interactivity, the framework supports exploratory data analytics. Since the collaboration between the data scientists and the domain experts takes place in all steps of the process, the domain expert can explore different options of data model and analytical method with the help of the data scientists and discover hypotheses while interacting with the data. For example, the domain experts can propose to change the feature sets used in the data model to evaluate the predictive power of certain features in the data set.

After the analytics process is done, results are reported to the stakeholders or policy makers to help them make decisions about the learning environment. One of the biggest challenges in interpreting and using the results is that not all analysis produces actionable knowledge. Actionable knowledge is needed for policymakers to be able to initiate an action to improve the learning environment. For instance, no action can be initiated from a result that indicates that there is a high positive correlation between "academic success" and "GPA". More examples of non-actionable knowledge is when data scientists find correlation between student background (such as ethnicity) and being at-risk of not graduating on-time.

However, identifying different student behavior trends in taking courses or participation in activities can help domain experts to understand academic processes which lead to different behavior trends and take action if necessary. Having actionable knowledge makes it possible to help improving the learning environment using analytics results. This closes a loop which starts with the data collection from the learning environment and ends with applying obtained actionable knowledge to the learning environment [27].

The interactive exploratory learning analytics framework in Fig. 2 enables domain experts to not only explore and interpret the results of certain analytical methods, but also interactively analyze student data by exploring the content of the data model and choosing from a variety of analytic models, a process typically only performed by data scientists. This "human-in-the-loop" approach allows the domain experts to effectively leverage their domain knowledge and expertise at the critical junctures of the analytical process on heterogeneous student data.

Our interactive learning analytics framework contributes to the field by providing the following features:

1. Interactivity between the domain expert and the learning analytics process. The domain expert can directly interact with the analytics process, and refine the process by evaluating the usefulness and interestingness of the outcomes.
2. Productivity of the interaction between the data scientists and domain experts. In our framework, the domain experts collaborate with the data scientists to refine the data model and analytic model to generate more interesting and useful outcomes.
3. Directed exploratory data analysis. Domain experts can explore different options and combinations of data models and analytic models during the refining process. This allows them to take part in a directed exploratory data analysis to look for new

analytic opportunities directed towards generating more interesting and useful outcomes.

4. Agile analytics. Having an iterative refining process with the domain experts involved in the process makes analytics development very quick in comparison with traditional approaches.

4 Focus Groups

We held two focus group meetings during which we met with our College of Computing and Informatics (CCI) leadership team, faculty and advisors to discuss hypotheses about student risk and success based on and derived from student data.

The first focus group meeting explored how an interactive learning analytics approach can facilitate decision making pertaining to education policies and practices. The focus group members included the CCI college Dean, Associate Dean, and Chairs of Software and Information Systems and Computer Science departments. Our design and analytics team included three PhD students and three faculty members. During the focus group meeting, we performed an interactive data analysis session with the college leadership team using 10 years of our student data analyzed by an existing visual analytics system, EventFlow, which is designed to visually present aggregated sequences of events [28]. We chose to use Eventflow, a visual analytic tool, rather than a computational analytic tool because it affords the interactivity we achieve in our learning analytics framework.

In the focus group, we started by introducing the learning analytics process and presented our sequence visual analytics in EventFlow. Figure 3 shows a screenshot of the EventFlow application presenting the time to graduation and time to attrition for the different populations of students. During the presentation, we walked through some examples of student sequences to describe and interpret them. We also demonstrated some trends of attrition for different populations such as freshmen, transfers, male, and female students in CCI major using EventFlow.

During the meeting, participants were able to discover patterns pertaining to a group of students that enrolled in CCI but quickly transferred to other colleges, and looked more closely at individual student trajectories. This interaction led to discussions around new hypotheses related to college-level student attrition. The participants appreciated the ability to interactively analyze student data and build new hypotheses. They were more interested in a data-driven approach that enables them to find novel fine-grained actionable knowledge rather than approaches that reinforce hypotheses they expected to be confirmed.

The second focus group included faculty and advisors in addition to the academic leadership. The focus group members included CCI Associate Dean, Chairs of Software and Information Systems and Computer Science departments in addition to seven CCI faculty members. Our design and analysis team included two PhD students and four CCI faculty members. Similar to the first meeting we used the EventFlow application to present student sequences to the participants. We walked through some

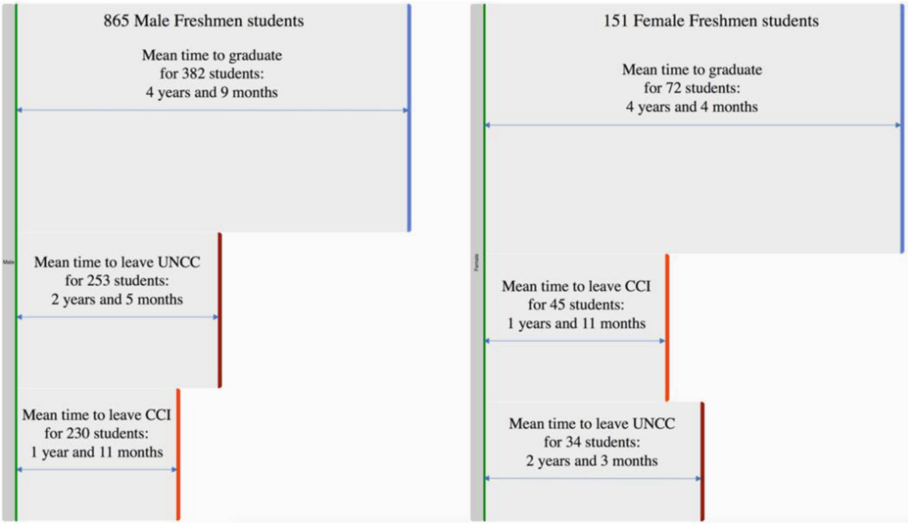

Fig. 3. An aggregate view in Eventflow showing the time for graduation and attrition for Freshmen students. The left timeline is for male students, while the right timeline is for the female students.

examples of student sequences and explained how the sequences can be interpreted in EventFlow.

This meeting, in contrast to the first focus group, was designed to engage the participants by asking them the following questions.

- What type of data would you suggest adding into the data model?
- What new hypotheses can you discover?
- What hypotheses can be generated for retention and graduation?

In the discussions, participants formed the following insights:

- Identify groups of students with a similar story and then try to find an intervention for each group.
- Analytically form clusters to find groups of similar students by discarding extreme low/high performing students.
- Find the difference between attrition patterns of all university students vs only CCI students.
- Extract statistical measures from the visual representation and confirm the statistics with the visual representation.
- Analyzing data after applying different filters such as part-time/full-time, transfers/freshmen, male/female, traditional/non-traditional, etc.

Overall, both scenarios engaged stakeholders with exploring and discovering new hypotheses. There was little interest in receiving the results of predictive or descriptive models without knowledge of how those models were formed and what source data produced the results. These focus groups reinforce the need for an interactive framework that affords iteration in the development of the student data model as well as the visual and analytic results and interpretation. While Eventflow facilitates iteration in the aggregation and visualization of the results, it does not provide affordances for changing the data model or selecting different features to be included in the data model.

5 Summary

Learning analytics is a developing research area and can benefit from research in other domains such as human computer interaction, data mining, and knowledge discovery that are struggling with making sense of big data. This paper contributes an interactive learning analytics framework inspired by the processes in data mining and knowledge discovery. This framework gives us the opportunity to investigate research trends and opportunities from a perspective of interaction and explorability. The trends in current research in learning analytics reveal a need for research that creates opportunities to include more agility in identifying salient data items to be included in the data model, to create alternative structures for the data models such as temporal models, and to include a broader range of predictive and visual analytic models.

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References

1. Chatti, M.A., Dyckhoff, A.L., Schroeder, U., Thüs, H.: A reference model for learning analytics. Int. J. Technol. Enhanced Learn. **4**(5–6), 318–331 (2012)
2. Gašević, D., Dawson, S., Siemens, G.: Let's not forget: learning analytics are about learning. TechTrends **59**(1), 64–71 (2015)
3. Greller, W., Drachsler, H.: Translating learning into numbers: a generic framework for learning analytics. Educ. Technol. Soc. **15**(3), 42–57 (2012)
4. Gašević, D., Kovanović, V., Joksimović, S.: Piecing the learning analytics puzzle: a consolidated model of a field of research and practice (2017)
5. Santos, J.L., Verbert, K., Govaerts, S., Duval, E.: Addressing learner issues with StepUp!: an evaluation, p. 14 (2013). https://doi.org/10.1145/2460296.2460301
6. Landrum, R.E., Gurung, R.A.R., Spann, N.: Assessments of textbook usage and the relationship to student course performance. Coll. Teach. **60**(1), 17–24 (2012). https://doi.org/10.1080/87567555.2011.609573
7. Bos, N., Groeneveld, C., van Bruggen, J., Brand-Gruwel, S.: The use of recorded lectures in education and the impact on lecture attendance and exam performance. Br. J. Educ. Technol. (2015). https://doi.org/10.1111/bjet.12300
8. Ma, Y., Liu, B., Wong, C.K., Yu, P.S., Lee, S.M.: Targeting the right students using data mining. In: Proceedings of the Sixth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 457–464. ACM (2000)

9. Minaei-Bidgoli, B., Punch, W.F.: Using genetic algorithms for data mining optimization in an educational web-based system. In: Cantú-Paz, E., et al. (eds.) GECCO 2003. LNCS, vol. 2724, pp. 2252–2263. Springer, Heidelberg (2003). https://doi.org/10.1007/3-540-45110-2_119
10. Morris, L.V., Wu, S.-S., Finnegan, C.L.: Predicting retention in online general education courses. Am. J. Distance Educ. **19**(1), 23–36 (2005)
11. Bravo, J., Ortigosa, A.: Detecting symptoms of low performance using production rules. In: International Working Group on Educational Data Mining (2009)
12. Romero, C., Ventura, S., García, E.: Data mining in course management systems: moodle case study and tutorial. Comput. Educ. **51**(1), 368–384 (2008). https://doi.org/10.1016/j.compedu.2007.05.016
13. Arnold, K.E.: Signals: applying academic analytics. EDUCAUSE Q. **33**(1), n1 (2010)
14. Arnold, K.E., Pistilli, M.D.: Course signals at Purdue: using learning analytics to increase student success, p. 267 (2012). https://doi.org/10.1145/2330601.2330666
15. Campbell, J.P., Oblinger, D.G., et al.: Academic analytics. EDUCAUSE Rev. **42**(4), 40–57 (2007)
16. Campbell, J.P.: Utilizing student data within the course management system to determine undergraduate student academic success: an exploratory study. ProQuest (2007)
17. Jayaprakash, S.M., Moody, E.W., Lauría, E.J., Regan, J.R., Baron, J.D.: Early alert of academically at-risk students: an open source analytics initiative. J. Learn. Anal. **1**(1), 6–47 (2014)
18. Macfadyen, L.P., Dawson, S.: Mining LMS data to develop an "early warning system" for educators: a proof of concept. Comput. Educ. **54**(2), 588–599 (2010). https://doi.org/10.1016/j.compedu.2009.09.008
19. Martinez-Maldonado, R., Pardo, A., Mirriahi, N., Yacef, K., Kay, J., Clayphan, A.: The latux workflow: designing and deploying awareness tools in technology-enabled learning settings. In: Proceedings of the Fifth International Conference on Learning Analytics and Knowledge, LAK 2015, Poughkeepsie, New York, pp. 1–10. ACM (2015). https://doi.org/10.1145/2723576.2723583
20. Han, J., Kamber, M., Pei, J.: Data Mining: Concepts and Techniques. Elsevier, Amsterdam (2011)
21. Geng, L.Q., Hamilton, H.J.: Interestingness measures for data mining: a survey. ACM Comput. Surv. **38**(3), 1–32 (2006)
22. McGarry, K.E.N.: A survey of interestingness measures for knowledge discovery. Knowl. Eng. Rev. **20**(01), 39 (2005). https://doi.org/10.1017/s0269888905000408
23. Zhang, Y., Zhang, L., Nie, G., Shi, Y.: A survey of interestingness measures for association rules. In: Proceedings of the 2009 International Conference on Business Intelligence and Financial Engineering, pp. 460–463 (2009). https://doi.org/10.1109/bife.2009.110
24. Bakharia, A., Dawson, S.: Snapp: a bird's-eye view of temporal participant interaction. In: Proceedings of the 1st International Conference on Learning Analytics and Knowledge, LAK 2011, Banff, Alberta, Canada, pp. 168–173. ACM (2011). https://doi.org/10.1145/2090116.2090144
25. Ferguson, R., Shum, S.B.: Social learning analytics: five approaches. In: Proceedings of the 2nd International Conference on Learning Analytics and Knowledge, LAK 2012, Vancouver, British Columbia, Canada, pp. 23–33. ACM (2012). https://doi.org/10.1145/2330601.2330616
26. Suthers, D., Chu, K.-H.: Multi-mediated community structure in a socio-technical network. In: Proceedings of the 2nd International Conference on Learning Analytics and Knowledge, LAK 2012, Vancouver, British Columbia, Canada, pp. 43–53. ACM (2012). https://doi.org/10.1145/2330601.2330618

27. Clow, D.: The learning analytics cycle: closing the loop effectively. In: Proceedings of the 2nd International Conference on Learning Analytics and Knowledge, LAK 2012, Vancouver, British Columbia, Canada, pp. 134–138. ACM (2012). https://doi.org/10.1145/2330601.2330636
28. Monroe, M., Lan, R., Lee, H., Plaisant, C., Shneiderman, B.: Temporal event sequence simplification. IEEE Trans. Visual Comput. Graph. **19**(12), 2227–2236 (2013)