A pedagogic method helps to create an actionable policy from big data through a PDCA cycle

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Abstract: Big data and learning analytics for higher education is a rapidly growing field with disruptive potential. However, there has been little research reported on a pedagogic method that helps to create an actionable policy from big data. In recent years, there is a meaningful debate that big data alone cannot improve teaching, and more research is needed from a pedagogic point of view. We, therefore, developed a pedagogic method called BDAL (big data for active learning) that helps to create an actionable policy through a PDCA (plan-do-check-act) cycle. It facilitates students to examine their goals and motivations, to improve learning styles, and to be an active learner. An experiment was conducted on 556 undergraduate students for a control group and an experimental group. With the help of BDAL, we were able to gain an actionable policy to improve education further both in and out of classrooms.

Keywords: actionable policy; active learning; big data; higher education; pedagogic method.


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1 Introduction

We are standing on the threshold of a revolution, where learners can be studied at a scale and fidelity which was previously impractical. Big data and learning analytics are
changing educational research into a data-driven science, and transforming institutions into organisations with evidence-based decision making processes. While big data is a broad term for data sets so large or complex that traditional data processing applications are inadequate, learning analytics is the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs (Call for the Papers of the 1st International Conference on Learning Analytics & Knowledge). We can take advantage of big data and learning analytics to improve student performance and raise instructor effectiveness while reducing administrative workload. As part of software-based and online classroom exercises and testing, the data on students’ performance keep increasing. There are other data sources such as social media, blogs, student-professor meeting notes, and student surveys. Institutions can benchmark their student, professor, and curriculum against other universities, yielding new insight into potential for improvement (Johnson et al., 2014; Shum, 2012; The Rise of Big Data in Higher Education; Pea and Jacks, 2014).

On the other hand, there has been little research reported on a pedagogic method that helps to create an actionable policy from big data. Discussions of big data in higher education typically have focused on the relative merits of analytics or technologies so far. Feldstein (2013) argues why big data alone cannot help teaching.

“Right now, what we are trying to do is a little like trying to conduct physics research before somebody has invented calculus. You can do some things around the edges, but you cannot describe the really important hypotheses about causes and effects in learning situations with any precision. And if you cannot describe them with precision, then you cannot test them, and you certainly cannot get a machine to understand them.”

Likewise, Reid (2013) raises the needs of research on a pedagogy between big data and the individual student. He argues that rather than being concerned about what big data can tell us regarding individual experience, we should turn our attention toward thinking about a pedagogy as something that shapes a massive, collective educational activity with data.

To address the above issue, we developed a pedagogic method called BDAL (big data for active learning) that helps to create an actionable policy from big data through a PDCA (plan-do-check-act) cycle. It has been implemented on several types of courses to help students to examine their goals and motivations, to improve learning styles, and to be an active learner. Data analysis accompanied by appropriate instructor’s intervention has improved students’ learning outcomes.

### 2 Previous work in learning analytics

Learning analytics has emerged as one of the most common terms to describe how we analyse big data in education, and improve systems through evidence-based adaptation. People view big data as a quantitative shift, but it is in fact a qualitative shift that demands a new way of thinking in education. This raises a host of challenges for the society at large, and for institutions seeking to make sense of this data (Johnson et al., 2014; Shum, 2012). There are a lot of recent articles and newly available information on big data and learning analytics (Educational Data Mining and Learning Analytics; Solar society for Learning Analytics Research). EDUCAUSE which is a prominent educational
association and organisation provides a rich source of information on big data and learning analytics (The Potential of Learning Analytics and Big Data). A ‘Policy Brief’ by UNESCO describes the impact of learning analytics at macro, meso and micro levels (Shum, 2012) that may work as benchmarks. Learning analytics workshop (LAW) project has identified key challenges and enablers for building the field of learning analytics (The Rise of Big Data in Higher Education). All the above works have made great impacts on our research on developing pedagogic methods to create actionable policies from big data.

2.1 Learning analytics as a digital nervous system

Institutions are increasingly sensitive to a digital nervous system that provides real time feedback on the external environment and the effects of actions. The key trait is to form an organisation’s feedback loop of digital data and to use it for a decision making process. The reach of digital nervous system has grown steadily over time, and agility and flexibility have increased with the growth of huge data sets and computational power (Dumbill, 2013). This enables an infrastructure that exploits rapid feedback, and informs more timely interventions whose impact can then be monitored. We need collective intelligence to interpret the signals and to adapt the system’s behaviour accordingly (Shum, 2012). Learning analytics plays an essential role in understanding how a digital nervous system should look like when we focus on learning processes as well as learning outcomes.

2.2 Level of analysis: macro, meso, and micro

The level of analysis are used in the social science to point to the location, size, or scale of a research target. Although they are not necessarily mutually exclusive, there are three general levels that research may fall into: macro-level, meso-level, and micro-level (Level of Analysis). In order to cope with the demands of new ways of thinking, it is important to understand those three levels, and to satisfy different requirements coming from each level.

2.2.1 Macro-level analytics

Outcomes of interactions over a large or global research population is traced. It seeks to enable cross institutional analytics, such as through state-wide data access to standardised assessment data over students’ lifetimes. Macro-analytics will incorporate more data from meso and micro levels, and become increasingly real-time. It can benefit from benchmarking and data integration methodologies developed in non-educational sectors (Shum, 2012).

2.2.2 Meso-level analytics

It indicates a research population size of an institutional level that falls between micro- and macro- levels. Meso-level also refers to analyses that are designed for connections between micro and macro-levels. Educational institutions can use tools integrating data in enterprise warehouses, analysing structured and unstructured data, generating dashboards, finding insights, predicting students churn, creating policies, optimising
workflows, and so forth. It is imperative to improve an educational and administrative process that affects students’ learning experiences and learning outcomes. Meso-level analytics should work well with macro and micro-level analytics so that data can be aggregated correctly and policies can be implemented effectively.

2.2.3 Micro-level analytics

It tracks and interprets the smallest unit of analysis such as teaching and learning for individual learners and groups in the educational setting. It can provide the finest level of detail as fast as possible even in real-time. Big data may include personal online activity of browsing and clicks, interpersonal activity of social networks, and physical activity of geolocation. Researchers are adopting techniques developed from various fields to improve the performance of micro-level analytics, such as business intelligence, social network analysis, and online gaming, etc.

What we are beginning to see, as a next step, is an integration of macro, meso, micro levels. The longitudinal data of hundreds and thousands of learners’ interaction histories across cohort students, institutions, regions and countries enables macro and meso level analytics with an unprecedented level of fine-grained process data. The creation of large datasets enables the identification and validation of patterns that are more robust. The breadth and depth at the macro and meso levels add power to micro-analytics that improves the quality of predictive models and learner feedbacks. When educational data have been validated against a nationally aggregated dataset, each institution may have greater confidence in the predictive power of the model and key learner behaviours (Shum, 2012).

2.3 Key challenges and enablers of learning analytics

Learning analytics workshop (LAW) project has sought to bring together the strategies and insights from different fields and sectors to identify key challenges and enablers for building the field of learning analytics at scale (Pea and Jacks, 2014). The results of these deliberations and associated research work are represented and outlined as a set of recommendations. The topics consist of building a conceptual framework, asking critical questions, articulating and prioritising study, determining resources, and developing a road map. Throughout the work of the LAW project, the researchers have organised “key challenges and key enablers” as the following five areas.

2.3.1 Foreground the challenges of educators

In relation to the prospects of personalised learning, it is important to contribute valuable insights from the instructor such as what they need, and what may better enable their practices. Underlying the possibility of personalised learning is the creation of a set of shared technology services for providing information and tools that instructors and students can use together throughout students’ learning process.

2.3.2 Define success metrics for learners

Different educational stakeholders may have different success metrics for learners. Careful thoughts are needed on what outcomes should be measured, and which metrics
need further research and development for use in personalised learning systems. For example, high grades and completed courses that are on the pathway to students’ career readiness are important as success metrics. If learners are to become career-ready, retention in school and in challenging subjects is an essential part of metrics. However, increasingly, we are finding that there are other important measurable aspects of learning processes that serve as key drivers of learning and which are subject to intervention to improve its outcome. Among the topics of special attention are non-cognitive factors in learning such as engagement or motivation, academic persistence and perseverance, and self-regulation (Dweck, Walton, and Cohen, 2011). Another important topic is the mindset which means how a learner conceives of the nature of mind and intelligence. It could be an entity given as a trait or something improvable by appropriate practices (PDCA).

2.3.3 Create a model of the learner

An evolving model of the learner is at the centre of personalised learning. As learning activities become personalised, recommendations for learning resources or activities are aligned to the learner profile model. Early warning signals would bring teacher’s attention through inferences about risk factors associated with failing during learning process. In order to create an effective model, predictors should be sought for what is appropriate to support the learner’s progress. The classes of variables and data sources should be refined for building a learner model, including the knowledge, difficulties, and misconceptions of an individual. The model should be comprehensible to both instructors and students, in order to support intra-personal and inter-personal learning goals.

2.3.4 Establish a well-functioning research infrastructure

It involves the individual and community workflow of the science, such as research planning, data standards and interoperability, data collection and processing, and data analysis for evidence-based decisions and actions. It is necessary to learn from best practices from other disciplines in order to avoid reinventing the wheel. Since learning analytics is about human being, great care is needed in our data privacy policies and frameworks, and informed consent and other provisions of laws are required for protecting human subjects in research.

2.3.5 Develop instructors and educational leaders

The transformations of educational systems, when actualised, will bring about important consequences. Data literacy skill of an instructor will become an important requirement for teaching, as quality of data-enhanced decisions in the classroom will depend on the ability of an instructor to quickly make sense of data presented through learning dashboards. Instructors need not to be data analysts but will need to be trained in interpreting educational data in a way that will effectively inform their own instructional decisions. In this setting, an important skill of an instructor will be getting an insight by synthesising personal understanding of the classroom context with data presented through learning dashboards.
3 Actionable policy through a PDCA cycle

A policy addresses when and how much to pull the levers. Too often, institutions create a data policy without a clear understanding of purpose or feasibility since they are ignorant of their own big data. As a result, many data policies could be ineffective and even get in the way of processes. Therefore, as shown in Figure 1, we developed a pedagogic method called BDAL (big data for active learning) that helps to create an ‘actionable policy’ through a PDCA (plan-do-check-act) cycle. It facilitates students to examine their goals and motivations, to improve learning styles, and to be an active learner.

Figure 1  Actionable policy within a PDCA cycle

PDCA was made popular by Deming, who is considered to be the father of modern quality control. The concept of PDCA is based on the scientific method as developed from the work of Francis Bacon that can be described as a three step cycle of hypothesis-experiment-evaluation (plan-do-check) (PDCA). Deming added a step of ‘act’, as shown in Figure 2, and revised it as a cycle suitable for improvements and control of modern processes. In many cases, repeating the PDCA cycle can bring us closer to the goal in spirals of increasing knowledge of the system. This approach is based on the belief that our knowledge and skills are limited, but improving. When the key information is not known, the PDCA, as a scientific method, provides feedback to evaluate our hypotheses and to increase our knowledge.

Figure 2  Continuous quality improvement with PDCA

Source: Educational Data Mining and Learning Analytics webpage
In terms of PDCA, our ‘pedagogic method of BDAL’ corresponds to a ‘plan’, which is the starting point of a cycle. A ‘teaching and learning experience’ corresponds to ‘do’, which generates data that can be analysed and studied in the following step. ‘Big data analytics’ are performed on behavioural and cognitive data to get insights, which can be implemented as an ‘actionable policy’. To complete a feedback loop, a ‘pedagogic method’ is revised or created based on an ‘actionable policy’. As shown in the figure, every step is connected to other steps, and affects or is affected by others.

The previous works on learning analytics were mostly concentrated on the big data analytics (check) step, and did not pay enough attention to actionable policy (act) and pedagogic method (plan) step. Even though there have been some efforts to use PDCA as an educational framework, their research were limited at a particular course or discipline level and did not make use of big data generated from teaching and learning experiences (Rita and Lakshmi, 2009; Wang, 2012; Fuhou, 2009). Therefore it has been difficult to form an efficient four step PDCA cycle for the control and continuous improvement of the process.

A ‘pedagogic method’ is a very important step, since it affects ‘big data analytics’ and ‘actionable policy’ through ‘teaching and learning experience’. We believe the ‘pedagogic method’ has been a missing link in most of other learning analytics researches on big data. It is essential to note that the quality of behavioural and cognitive data heavily depends on a design and execution of a pedagogic method. In the following, we described how the four step PDCA (plan-do-check-act) cycle is implemented in our system, and presented our pedagogic method in the next section.

3.1 **Pedagogic method (Plan)**

- Establish the pedagogic objectives and processes necessary to deliver results in line with the goals.
- Facilitate students to examine their goals, motivations and learning styles, and to use strategies to be an active learner.
- Improve the completeness and accuracy of the pedagogic specification as part of the targeted improvement.
- Develop or adjust the pedagogic method based on feedback from the actionable policy step.
- Start on a small scale to test possible effects, if possible.

3.2 **Teaching and learning experience (Do)**

- Develop the pedagogic plan, execute the process, and get results by creating teaching and learning experience.
- Transform educational systems to personalised learning.
- Make interactive data-enhanced decisions in the classroom to quickly make sense of data presented in learning dashboards.
- Synthesise instructor’s personal understanding of the classroom context and apply it to teaching and learning experience.
3.3 **Big data analytics (Check)**

- Analyse the educational data which were measured and collected during teaching and learning experience and compare against the expected results targets or goals from the pedagogic method to ascertain any differences.
- Look for deviation from the pedagogic method and also look for the appropriateness and completeness of the pedagogic method to enable the execution.
- Process educational data to see trends over several PDCA cycles and to convert the collected data into information that you need for the next step (actionable policy).

3.4 **Actionable policy (Act)**

- Adjust and request corrective actions on significant differences between actual and planned educational results.
- Analyse the differences to determine their root causes, and create an actionable policy.
- Determine where to apply changes in a pedagogic method that will include improvement of the learning process or outcomes.
- Refine the PDCA cycle to improve with more detail in the next iteration of the cycle.

4 **Pedagogic method**

Discussions of big data in higher education typically focus on the relative merits of analytics or technologies. Feldstein (2013) argues why big data alone cannot help teaching, and Reid (2013) raises the needs of research on a pedagogy between big data and the individual student. To address the above issue, we developed a pedagogic method called BDAL (big data for active learning) that helps to create an actionable policy through a PDCA (plan-do-check-act) cycle. It has been implemented to facilitate students to examine their goals, motivations and learning styles, and to use strategies to be an active learner. Data analysis accompanied by appropriate instructor’s intervention played the key role to understand and improve students’ learning styles.

With the help of big data analytics, instructors encourage students to become active learners by providing opportunities for students to reflect on their motivation and use of strategies in learning. First, BDAL aims to find a motivation model for students and set up pedagogic strategies for each student and students as a whole. Second, it tries to identify student’s performance and learning style to understand how they perceive and process information in different ways, and tailor advices for each student or groups of students. Third, it encourages students to compete and cooperate each other by doing assignments and projects together, and to interact with other groups both online and offline. Fourth, it helps an instructor how to orchestrate and intervene students’ learning process by providing various information. Fifth, using exploratory and confirmatory factor analysis on years of data from nationwide measurements, it helps to examine the structure and characteristics on students’ approaches to learning. Finally, with all the above steps of BDAL, instructors search for pedagogic strategies and actionable plans to create virtuous cycles of learning.
4.1 Motivation

- Motivation influences how and why people learn as well as how they perform.
- BDAL helps to create profiles of motivation and attitudes based upon personality measure, self-storytelling, areas of interest, and school performance.
- An instructor can use analytics of Big-Five personality traits (John and Srivastava, 1999) to set up pedagogic strategies for each student and students as a whole. For instance, when openness values are high, instructors may provide more creative projects to motivate students. When neuroticism values are high, instructors may use clickers more to check and motivate students understanding of the subject.
- The instructor can also make use of research results from respectable organisations such as ETS. They have announced a report on Big-Five research between academic and workforce outcomes (Relationships between Big Five and Academic and Workforce Outcomes). Those findings are useful in developing pedagogic strategies to motivate students.

4.2 Performance and learning style

- Big data can be obtained on student’s performance with tests and be analysed to identify students’ learning styles. Analysed results help to understand how he or she perceives and process information.
- The survey from Longitudinal Evaluation of Advancement of College Education has been used to understand students learning styles (Bae, 2012). For performance measure, GPAs and performance tests have been used.
- Instructors may create a profile on the student’s learning behaviours and habits and to develop recommendations and learning materials in problematic subject areas.
- Based on the learning style analysis, the pedagogic strategy of competition and cooperation can be used for individual and small group projects.

4.3 Competition and cooperation of group work

- If properly controlled, competition and cooperation of group works can create great synergy effects.
- In BDAL, projects are formed in a small group of two or three students, while project discussion and evaluation in classroom are formed in a group of four to six. The small group is formed in a heterogeneous way that educational backgrounds between group members are different to each other.
- It helps to leverage cohort analysis for groups of students that can collaborate inside and outside of the class to improve individual performance, cohort assignment, and interaction between groups.
- Students are encouraged to access other students’ group works on cloud database, compete and cooperate with them. They may integrate what they learned from other students in their final projects.
4.4 Instructor’s orchestration and intervention

- Advocates of traditional TBL pedagogy claim that free-rider problem is the result of poorly-designed group assignments, and ask for responsibilities of instructors (Team Based Learning).

- BDAL pedagogy asks each student (not the instructor) to be responsible in choosing their own assignments or projects that will influence the outcome of their final (individual) project.

- Instructor’s role is close to orchestration behind the curtain. When students are motivated, they showed more satisfaction about choosing their own assignments and project that will lead toward their final project.

- When classroom discussions are in progress at the same time, instructors can interact with groups of students one by one or all at once. Sometime real-time data and analysis were used to promote students interaction both online and offline, which turned out to be a very useful pedagogic strategy. Benchmark results show that student faculty interaction (SFI) factor has improved significantly with this method.

4.5 Leveraging private and open source data

- The data from the nationwide report can be compared with BDAL data to compare benchmarks of ours against others as shown in the next section.

- The goal is to identify weak or strong areas of operational and educational performance, and to undertake an actionable plan to improve education.

4.6 Virtuous cycles of learning

- Here we define virtuous cycles of learning as a self-propagating favourable situation in which a successful learning leads to a desired result or another successes in a chain.

- We believe in creating virtuous cycles of learning which an ideal goal worth striving for is. Without big data analytics in higher education, it would be almost impossible to develop a pedagogic method for virtuous cycles of learning that each student can benefit from.

- With BDAL, we helped some students to transform and reached at the primitive stage of virtuous cycles where they can study and research by themselves to solve quite difficult (and demanding) problems. We are interested in finding which pedagogic methods work on whom, and develop case studies as a theory.

- BDAL is only at the beginning stage of a longitudinal study. As more data are accumulated and analysed, we expect to find more interesting results and to improve our pedagogic method further.
5 Working examples of an actionable policy

An experiment of actionable policy was conducted between 2013~2014 on 556 undergraduate students for a control group (non-BDAL) and an experimental group (BDAL). We surveyed students to assess the extent to which they engage in educational practices associated with high levels of learning and development. The survey questionnaire was based on the research of advancement for college education (ACE) by the Korean Ministry of Education (Bae, 2012) on nationwide 18,122 undergraduates. As shown Table 1, the benchmark scores of BDAL group was higher on most of the key factors than the scores of other groups (non-BDAL in a university and non-BDAL in nationwide universities in ACE research).

Table 1 Benchmark measures of advancement for college education (ACE)

<table>
<thead>
<tr>
<th>Level</th>
<th>Macro</th>
<th>Meso</th>
<th>Meso &amp; Micro</th>
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<tbody>
<tr>
<td></td>
<td>Compare group</td>
<td>Control group (Non-BDAL)</td>
<td>Experimental group (BDAL)</td>
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<tr>
<td>2012 ACE N=18,122</td>
<td>2011 N=207</td>
<td>2012 N=219</td>
<td>2013~4 N=130</td>
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<tr>
<td>Group</td>
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<td>M  SD</td>
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<tr>
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<td>10.6 3.7</td>
<td>3.5 10.8</td>
<td>3.4 3.7</td>
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<tr>
<td>ILA</td>
<td>11.4 2.8</td>
<td>2.6 13.6</td>
<td>2.6 2.8</td>
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<tr>
<td>ACL</td>
<td>11.2 2.6</td>
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<td>2.3 2.6</td>
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<tr>
<td>PR</td>
<td>10.9 2.8</td>
<td>2.6 10.5</td>
<td>2.7 2.8</td>
</tr>
<tr>
<td>SFI</td>
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<td>13.3 3.7</td>
<td>14 4.2</td>
</tr>
<tr>
<td>SCE</td>
<td>8.8 2.5</td>
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LAC (level of academic challenge), ILA (intellectual learning activity), ACL (active/collaborative learning), PR (peer relationship), SFI (student faculty interaction), SCE (supportive college environment).

Figure 3 shows measured results for comparison between a BDAL group (solid line) and non-BDAL groups (dotted lines). Students reported significant increase in the level of academic challenge (LAC), intellectual learning activity (ILA), and active and collaborative learning (ACL). This can be explained through improvements in motivation, learning styles and active learning attitude. It is worth noting that benchmark scores for student faculty interaction (SFI) has risen without increasing office hours. Instead, the quality of interaction based on data analysis has provided effective communication methods between students and faculty. For peer relationship (PR), we found that just increasing the amount of group works do not improve the scores as much. Without the instructor’s intervention, students would group a team based on their familiarity of each other throughout their whole school life. We even observed that many students take classes together strategically so that they can perform group projects and get better grades. To alleviate this problem, in the following semester, we changed a program so that student group members come from different backgrounds and are not familiar to each other. As a result, the score on peer relationship (PR) factor has improved significantly, which we could not achieve before with other methods. While
some students evaluated that it was a great opportunity to understand other student’s point of view who they do not usually communicate, there were others who felt it is not fair for the instructor to deprive of their rights on choosing partners in group works. This result caused us to start an interesting policy research on how to compose members of group work effectively based on student’s academic behaviour, performance, and learning styles. The last factor on the table is the supportive college environment (SCE), such as administration, resource management, and policy making. Because most of the administrative work was related to the indirect support for students, it was very hard to let students notice improvements on supportive college environment. To address this issue, we are developing a program to make use of big data to support students education outside of classrooms so that they can find greater support in non-traditional sectors of college environment.

Figure 3  Comparison of measures of advancement for college education (see online version for colours)

6 Conclusion and future research topics

Big data and learning analytics in higher education is changing educational research into a data-driven science and transforming educational institutions into organisations that make evidence-based decisions and policies. There are opportunities for universities and colleges to make use of big data to improve student and faculty performance. All can benefit from sharing big data analytics and best practices (Iansiti and Richards, 2012). A fundamental objective of our research is to provide university faculty, staff, and college with leadership through a pedagogic method that helps to create an actionable policy through a PDCA cycle. Our research findings offer compelling evidence that positive
change is taking place, and that the possibility is not limited to conventional pedagogic thoughts.

We believe our pedagogic method is a very important step in PDCA cycle, since ‘pedagogic method’ step affects ‘big data analytics’ and ‘actionable policy’ steps through ‘teaching and learning experience’ step. However, unfortunately, a pedagogic method has been a missing link in most of learning analytics researches on big data. It is essential to note that the quality of behavioural and cognitive data heavily depends on a design and execution of a pedagogic method. Even though our method was successful in its own right, the implementation part left a lot more to be desired. We faced open problems in algorithms, including - but not limited to - natural language processing, Bayesian statistics, and data variety and context. Critical debate is needed on the limits of computational modelling, the ethics of big data analytics (Alstete and Cannarozzi, 2014), and the educational paradigms that big data in higher education promote.

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Pedagogic method


