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Shifting Actors and Shifting Audiences: From Academic Analytics to Learning Analytics

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Abstract—Learning analytics (LA) is an emerging field in which data is collected and analyzed to assess students’ classroom behaviors. As an attempt to quantify or predict student success, LA can be used to begin to unpack the “black box” resulting from increased use of academic technologies. LA’s origins, however, are in the earlier field of academic analytics (AA). The two approaches diverge, however, in terms of the audiences that they target, and in terms of the actors called upon to put their implementations into place. This paper seeks to resolve the conceptual distinction between the two methods by examining a host of individual tools that represent possible first-generation LA implementations. From these examples, a model of the ideal actors and audience for LA is extracted, with a theoretical discussion of its possible implications.

Keywords: learning analytics; academic analytics; educational technology; learning analytic tools; early warning systems

I. INTRODUCTION

In many ways, the field of learning analytics (or LA) should be considered new. LA is broadly defined as the effort to improve teaching and learning through the targeted analysis of student demographic and performance data [1][2]. The field itself has come into being largely thanks to the proliferation of digital data produced by educational institutions’ increasing tendency to produce, submit, and assess academic work in electronic form [3][4]. While the first formal conference on LA, held in 2011, is evidence of its growing relevance in educational circles on an international scale, the fact that such a conference had not existed previously is sign enough of LA’s relative infancy.

Yet for all the budding interest in LA, its earliest implementations have evolved from older models and methods, from raw data mining (cf. [5]) and learning community studies (cf. [6]) to the broader field of academic analytics [7][8]. Academic analytics (AA) in particular might be seen as the formal precursor to the LA focus. While AA sought to benefit the business side of education, deploying statistical modeling to increase institutional efficacy (cf. [9]), LA ideally attempts to apply predictive models to provide insight into the actual processes of learning. Whereas successful LA implementations might well lead to more cost-effective decisions, it would do so only as a byproduct of its focus on classroom activities; likewise, while successful AA systems might lead to improved classroom performance, this would in most cases only be an intermediate benefit, not the immediate goal. Put differently, LA is micro where AA is macro: providing insight into behaviors within the classroom rather than into the circumstances that allow that classroom to exist. This distinction can best be expressed by an understanding of the different audiences that each field targets, and the different actors called upon to put its implementations into place.

While the distinction between LA and AA is conceptually clear, the division appears to break down somewhat in practice. As institutions and educators increasingly begin to install LA systems, they often tend to employ frameworks inherited from academic analytics. Even nominal attempts to directly improve learning and teaching practice (as in [10], to take just one example) tend to digest institutional systems data with limited understanding of how that data could or should inform pedagogy. Although AA remains a vital and valuable field, it needs to be acknowledged that LA and AA approaches have different priorities, different intended benefits of the technology, and different personnel meant to put that technology into practice. Growing the field of learning analytics requires making sure that it remains distinct from what came before and that its purpose remains rigorously clear.

This paper attempts to clarify the distinction between LA and AA, both in theory and in practice, by presenting a model of the audiences and actors involved in either implementation. Sections II and III of the paper discuss the conceptual motivations of academic analytics and learning analytics. Section IV examines the transition from academic to learning analytics by way of specific examples. Building from these examples, Sections V and VI examine the actors and audience required of learning analytics. Section VII presents the model for the actors and audience involved in optimal learning analytics implementations, as well as a comparison of how this model applies to the examples noted prior. The final section concludes the paper and discusses possible consequences of the LA and AA dichotomy.

II. ACADEMIC ANALYTICS AND THE BUSINESS OF EDUCATION

Academic analytics (AA) is defined as the marrying of data pertaining to retention and graduation with statistical techniques and predictive modeling in order to improve long-term educational strategy [11]. Itself descended from the practice of “business analytics,” AA was first introduced as a means of providing enhanced accountability in higher education [11][12], and is particularly useful in supporting the financial and business functions of the academy [7]. In order
to gain an advantage over competitors, information is gathered, analyzed, and manipulated in order to produce results that explain how a specific service or product can be optimized [11]. The demographic information modeled by AA turns the educational processes of the school or university inwards, by noting, for instance, similarities between students who had failed to graduate, allowing the institution to prevent those same conditions from occurring in the future.

While current students provide the data for analysis, they are not necessarily, however, the intended target of reform. Since this kind of analysis examines student data made most visible over the duration of a student’s academic career, its benefits accrue primarily in the long term. The concept of AA generally centers around the efficacy of an institution’s ability to produce successful students and to gauge how well material was ingested and retained. The product resulting from AA is then used as a means of determining effectiveness of faculty and course material, and ultimately, the success of an institution in fostering measurable student intellectual growth [11]. In this model, one might say that upper-level institutional administrators are both the audience for academic analytics – the ones who primarily benefit from its data – as well as the actors responsible for putting it into place.

III. LEARNING ANALYTICS AND THE “BLACK BOX” OF EDUCATION

At its best, LA offers insight into what might be thought of as the “black box problem” of education. Traditionally, student progress is only judged by a comparison of their earliest and eventual knowledge, as given by pre-tests and post-tests of material; a student who enters a course with a C-level understanding of calculus and exits with an A-level understanding can be said to have learned something. Yet between entry and exit, any number of activities – practice problems, class discussions, response papers – actually took place, and it’s these activities that contributed directly to the student’s learning. Given the near-ubiquitous use of academic technologies (like learning management systems) in educational institutions, many of these activities have transitioned to an online platform. As a result, much of the learning that takes place occurs in an arena where the instructor is not always present, rendering the actual learning taking place during that activity rather opaque. The “black box” of education is how those activities contribute to the student’s development: which behaviors, and how and why these behaviors, led to learning. LA looks to capture what is inside this black box and to makes it contents clearer.

As opposed to AA, while students again provide the data for LA, they are now, in many cases, its intended audience, and individual instructors are the actors charged with carrying its reforms out. The foundational conceptualization of LA is driven by a motivation for benefits to students, practicality for instructors (e.g., intervention and up-to-date grading), and for pedagogical and instructional efficiency on a micro level, which may ultimately prove beneficial for the institution [4]. Again, this is in opposition to the broad approach of AA that functions at a higher institutional level.

LA serves as a means of determining student behavior throughout a course and creating predictive models based on that behavior. By extension, it can aid in maximizing both student and faculty performance and determining pedagogical approaches to be adopted for the benefit of students and educators. In short, LA is a bottom-up, micro approach, where benefits are meant to accrue primarily in the short term. Those implementing LA are concerned with the dynamic interaction of teachers, learners, and learning material as itself the central focus in the educational process. The data stemming from LA then might be used to inform current or future pedagogical practice. In this sense, LA does not cater to any one learning model. LA may be used to examine a particular learning model and the subsequent data may impact pedagogical approaches, but the purpose of LA is to be versatile in the ways it is used to study black box of learning. Indeed, it is this versatility that allows for in-depth observations and analysis to be made on the varied facets of student learning.

LA in practice yields insight into the behaviors, interactions, social aspects, and so on that occur throughout the student’s learning experience. It’s at this nexus that LA differs fundamentally from AA. Academic analytics provides a macro (or, long-term, top-down) understanding of the inner machinations of an institution, by taking a broad view of the academic process, as given by students’ progress from recruitment to graduation, class sizes, personnel considerations, and cost-effectiveness [11]. This is not to say that LA never results in improved conditions such as cost efficiency, but the micro focus of LA provides a more nuanced perspective on the individual classroom environment. In doing so, LA in action hones and polishes one of the facets of AA. Examining the behaviors and processes of students throughout their time in a course shifts the focus from the broad definition of “academics” to the individual student. LA can potentially create an educational environment that better the academic atmosphere for both student and instructor by streamlining the classroom experience.

IV. NARRATION OF THE FIELD: ASSESSING THE EXISTING PLAYERS

In many ways, LA wouldn’t be possible without the earlier existence of academic analytics. As a concept, LA has taken shape by the tools created to implement it [13] [1]. But because these tools are built on statistical models, they rely on data produced by something. The near ubiquity of institution-wide academic technology [14], like the learning management systems (LMS) such as Blackboard or Moodle that provide students and faculty with a digital gateway to course content and administrative features, means that this data has conventionally been derived from the same routines that produce academic analytics (as in, for instance, [10]). Many tools that attempt to approach the black box of education are thus inflected with what might be seen as an AA-specific mentality. As noted previously, the difference lies in the focus of the tool, the actors that are intended to use it, the audience that it is intended to benefit, and whether those benefits are accrued in the short- or long-term.
A host of individual tools, developed separately at a number of different institutions, demonstrate just part of the possible scope of first-generation LA strategies. While these tools target a variety of different data sets, it is in the range of their individual implementations that some of the possibilities of learning analytics are most broadly expressed. Even among these varied examples, certain dominant traits emerge that might inform our understanding of what an optimal LA strategy might yet be.

The following four tools were chosen for several reasons. Conceptually, the amalgamation of these tools is representative of the functions and goals of LA. All tools, with the exception of the Point of Originality, were implemented without LA as a pedagogical foundation. However, they show what current LMS tools are capable of and in what ways these functions can be reshaped or reoriented to fit the needs of LA.

Although the functions may seem somewhat scattered, each tool incorporates the dynamic of the audience and actor that is the focus of this paper. They also act to understand the limits of the adaptability of preexisting and university-specific AA/LA tools. Each tool incorporates some form of real-time feedback but Moodog, for instance, has both the students and the instructors as the actors and audience whereas the Point of Originality tool has the instructors as the actors only. The real-time information that students receive in the Check My Activity tool is theirs to act upon for intervention; it’s not the instructor’s duty to implement a new course of action. In other words, the tools below have similarities but also differ from one another in certain ways. The goal is to present how some universities have approached their individual LMSs and adapted them for specific uses and in what ways, ultimately, these uses can be shaped for LA.

A. Early Warning System

The first of these tools is the early warning system developed in a study by Macfadyen and Dawson [15]. Given the large amount of information continually collected by an institution’s LMS throughout the semester, the authors, building upon the work of others, sought to devise a way in which this data could be visualized in a meaningful manner for instructors. The goal was to create an early warning system that would allow real-time updates on students and a means of intervention, if necessary. They assert that presently, the only way to gain meaningful analysis is through cumbersome manual processes given that LMSes offer limited reporting options despite their tracking and information-acquiring abilities [15]. Additionally, no guidance exists for instructors on how to interpret data in a pedagogically useful way.

Using specific data collected from the LMS (Blackboard, in this case), a number of key indicators were examined. Several variables potentially correlated, including: total number of online sessions, total time online, total number of discussion messages posted, time spent on assessments, and time spent on assignments. Some of the variables contained sub-variables (e.g., for the total number of discussion messages posted, the number of new messages posted was tracked, as well as replies, uses of the search function, etc.).

Their results, while too comprehensive to summarize in the current discussion, included evidence that three specific measures, number of forum postings, mails messages sent, and assessments completed, function as significantly predictive variables of a student’s final grade. Logistic modeling demonstrated that a predictive model developed using these variables correctly identified students at risk of failure with 70.3% accuracy and correctly flagged as at risk 80.9% of students who failed the course [15].

This data showed that predictive modeling is possible and that certain variables can indicate success or failure. This information could then be made available to an instructor through a dashboard interface for intuitive perusal.

B. Check My Activity

The Check My Activity (CMA) tool was implemented at the University of Maryland and is similar to the early warning system discussed in [15]. A study of the tool [2] determined that low-to-failing course grades correlated to students’ decreased use of a learning management system (LMS). Therefore, the primary function of this tool was to allow students to track their usage behavior on LMSes. Equipped with this tool, students had the ability to observe their LMS behavior and to take the necessary steps to increase usage, if necessary.

The CMA tool “allows students to compare their own activity in the Blackboard LMS against an anonymous summary of their course peers any time they want.” Additionally, after the instructor posts their grades, students can view the grade distribution report that will show their activity with their peers who earned the same, higher or lower grade [2].

As the study notes [2], personalized activity reports may be able to “say” to students what they would or could not hear from their instructor or academic advisor. With this knowledge, students can gain a sense of how their LMS activity may impact their grade. The CMA tool differs from others in that the burden of monitoring progress falls on the student. They must check their status, their grade and activity in relation to their peers, and must decide independently what to do with that information.

C. Moodog

The third tool to consider is called “Moodog,” short for Moodle Watchdog. Developed for use in the spring of 2006 at the University of California, Santa Barbara, Moodog was the response to the researchers’ perceived issues with LMSes that lack the comprehensive function to track, analyze, and report students’ online learning activities [16]. If equipped with a tool capable of these functions, the instructor would be able to monitor how students interact with online material, by focusing on either the class as a whole or individual students. A tool of this sort gives students the ability to view their progress in reference to other students in the course. Moodog’s goal was to provide important insight into student usage of online materials by generating aggregated and statistical
reports; visualizing the results; identifying activities students have and have not performed; and reminding students to download material not yet accessed.

Students, for instance, can see popularity bars that indicate what materials other students found most useful. The authors reason that this function will encourage students to check popular materials they may not have checked, but also more frequently than in the past. Since the information can be collected during the semester and analyzed in real-time, instructors can potentially observe the processes of student access of material throughout the course itself. This would allow for a careful tailoring of the course for future students.

The case study provided in the preliminary research presented the various functions of the tool and provided an experimental overview of the capabilities of Moodog. However, the functions of the tool were displayed and certain factors could be pulled from the visualized data pertaining to which materials students were most drawn to versus those that were least accessed, for example. The benefits were tangible in that results were derived in real time from the tool and analyzed by the instructor without the need for knowledge in statistical analysis.

D. The Point of Originality

The final tool to examine is the point of originality [17]. While previous tools discussed dealt with information gathered throughout the semester and more general data mining and analysis, the Point of Originality tool can be used to score, on what may be considered both qualitative and quantitative levels, students’ writing in terms of their “originality,” as given by their ability to place course concepts into their own, original words. Ultimately, the purpose of the tool is to provide the instructor with a means of scoring and quantifying the original material discussed within a blog posting. Given that reading individual blog posts is a time-consuming activity, the Point of Originality tool allows the instructor to monitor class activity with the capability to extrapolate the progress of each individual student. Another purpose of the tool is to equip educators with a method of handling the steadily increasing class sizes that institutions are facing [18].

In short, the instructor inputs an important course concept or phrase. The tool then employs a process analogous to the educational process of recasting: using the complex lexical associations between words, the tool calculates whether the students’ writing has been able to place the course concept into their own words, and thus brought the students nearer to mastery. This process recreates the same kind of cognitive activity that an instructor would undergo, yet in an automated manner that is far less time-intensive [17]. Visualization of the data allows the instructor to pinpoint which students might be less “original” in their phrasings than others, and to make adjustments to the syllabus as needed.

V. THE ACTORS IN LEARNING ANALYTICS

As a general concept, learning analytics offers the ability to peer inside the black box that makes up students’ individual learning experiences. Yet when this concept is transformed into a usable tool, this power must be applied by an actual person, be it an instructor, an administrator, or the students themselves. These personnel might be thought of as the actors called upon to put LA interventions into place.

The role of the actor is not an arbitrary judgment. In the same way that learning analytics has grown out of the tools developed to utilize it, the individual actors optimally suited to learning analytics are a function of the types of things that the tool might most effectively accomplish. Even in the tools already discussed above, clear patterns for use emerge.

Many of the noted LA systems are implemented with the goal of creating predictive models of behavior for instructors and with functions that allow for intervention when needed. The accumulation of real-time grading and monitoring gives instructors insight into the status of each student’s progress throughout the course. The Moodog program, for instance, helps professors gain a sense of class and individual student activity [15]. Moodog, as it collects information, can analyze the grades of individual students and whether or not they have accessed certain materials online. If there is a lack of activity in one particular online resource, the program will send an email reminder to those students reminding them to access said materials. Similarly, the Point of Originality tool allows instructors to monitor which students exhibit the most sophisticated understanding of the course material, and to anticipate which students might struggle with upcoming assignments. With either the Moodog or the Point of Originality tool, the instructor is presented with the data from analysis, and can use that data to make pedagogical changes in the short and long term respectively.

Many of these tools also offer the potential to provide continuous monitoring, thereby alleviating the instructor’s need for constant vigilance. As the growing number of densely populated classes increases, LA offers the opportunity to survey large segments of student activity. The early warning system (see Section A) for instance, provides instructors with an indication of which students might be falling behind, and gives students and instructors alike an opportunity to act on that information. These systems optimally automate the same cognitive processes that an instructor would ordinarily undergo, yet without necessarily directing the same amount of attention to every individual student. This is not to substitute an instructor’s vigilance in the course, however, it allows for more freedom in gateway courses where the number of students is high. In a number of these tools, an instructor can critically analyze the effectiveness of the different aspects of his or her course. Determining which online function or material is utilized the least may allow the instructor to gain an evaluation of that aspect from students as to why it was underutilized. Alternatively, discovering frequency of posting in particular sections of a discussion forum can yield insight into which subject matter students were most engaged in. The tools of LA equip instructors with varied knowledge about their students’ activities, which may impact the design of a course.

Strategies for actors in learning analytics can best be summarized by the following list:
1. LA tools can serve as a means of continuous monitoring, acting as an early warning system so that instructors might keep track of class participation and performance without constant vigilance.

2. Using rolling data collected throughout the semester, LA tools can allow instructors to perform targeted interventions, working with individual students or making changes to pedagogy as necessary.

VI. THE AUDIENCE OF LEARNING ANALYTICS

As given by the problem of the black box, ideally, the audience that should benefit from LA is the immediate classroom population, perhaps as some combination of students and instructors, but ultimately always the students themselves. The cyclical dynamic between the two has potential to yield the most important and useful information. Tools like the Point of Originality seek to streamline the instructor’s activity, but only so that the instructor can respond in a way that benefits learners. This focus highlights LA’s attention to the very sorts of interactions that characterize the black box problem. The Check My Activity tool, likewise, presents its activity reports to both students and instructors directly. Other tools, like Moodog might be concerned with individual classroom engagements, but are generally of most use when projecting for future iterations of the course. Cases like these somewhat resemble the earlier focus of academic analytics, where while some utility remains with the classroom audience, additional utility is deferred for long-term planning.

Implementation of LA on a practical level is made easier by the proliferation of information-gathering academic tools. In many cases, the learning management systems already in place provide the technological foundation on which to build, add, and manipulate already existing software to suit the needs and desires of the institution, instructors, and students. While these systems generally serve the purposes of academic analytics, their entrenched status allows for rapid implementation of certain tools (such as Moodog’s integration with an existing Moodle system). As a result, many tools currently in place as AA systems can be repurposed as LA tools, yet it is nevertheless important not to lose sight of LA’s specific focus on the classroom environment itself. LA’s conceptual focus allows it to make use of existing data structures in order to benefit the important dynamic between teacher, student, and materials.

Many of the tools examined above were, developed to be institution-specific, i.e., Moodog at University of California, Santa Barbara, and the Check My Activity (CMA) tool at the University of Maryland, Baltimore County. Though they were developed based on the LMS already in place at the university, it could be argued that other institutions with the same LMS could also implement that given tool. This is important to note because it allows benefits of a tool or system to more stably transfer to other institutions. Since many of these tools likewise utilize data-mining features in order to report on the use of LMS systems, LA tools might further indicate how certain parts of the LMS system might be enhanced.

The integration of LA approaches with existing system makes further allowances for the technological understanding and capabilities of the instructor. The increased reliance on technology adds an expectation of technological competency on the part of the instructor. Thus many implementations attempt to streamline their presentation of data, displaying information in ways that are intuitive and user-friendly. Some systems already in place, such as Moodog, are created to be user-accessible and highly automated. The Point of Originality tool is designed in the same fashion in order to allow for a quick comprehension of the functions and capabilities of the tool. This reduces the amount of pressure on the instructor to gain an understanding of a new technology. In short, simple interfaces, built upon the very LMSes that instructors are presumably already familiar with, reduces potential barriers to access.

Along with the capacity of visualize data comes an enhanced ability to place the tool in the hands of a broader group of users. Access to the tool through user-interfaces allows for rapid familiarization with the tool, less need for a comprehensive grasp of interpreting data, and potentially less time-consuming access to the information sought. As a result, the tools are made accessible to the actual people intended to benefit from them.

Strategies for the audience in learning analytics can best be summarized by the following list:

1. The audience of learning analytics is the immediate classroom itself.
2. Data visualization is used to facilitate the comprehension of large amounts of information.
3. The tools developed by LA are user-accessible, and available to the people who stand to benefit from them.

VII. THE MODEL FOR ACTORS AND AUDIENCE IN LA AND AA

While the line between learning academics and academic analytics is blurred by a handful of the implementations cited above, the distinction between the two might be reduced to two related questions: who is the audience for the tool, and who are the actors meant to put its suggested reforms into place?

This dynamic most comprehensively accounts for the macro and micro dynamics on which AA and LA are respectively framed. Both approaches make use of student data and student activity in order to make judgments about educational efficacy. Yet because academic analytic tools are most frequently deployed in school-wide administrative
systems (like a CMS or LMS), the tools themselves are primarily in the hands of the institutional administrators who oversee the university’s business apparatus. The institution itself, broadly defined, is the actor responsible for implementation. What’s more, the feedback from AA systems is primarily aimed at benefiting the institution’s long-term financial and educational missions. The main audience for AA data is thus likewise the institution as a whole.

In learning analytics, however, student activity is turned towards a different end. A variety of stakeholders, from educators to the students themselves, are responsible for digesting the LA system’s input. In early warning systems, for instance, the need for pedagogical intervention is brought to the attention of both students and instructors, and while students can take it upon themselves to alter their behavior, it is the individual instructor’s task to deploy more thorough interventions as necessary. The teachers and learners within the classroom, then, are the actors responsible for translating LA feedback into real-world results. The audience for this information, however, is always aimed at the students themselves. The whole point in conducting an early warning intervention is so that students that are struggling at a precise moment can be coached to rectify their mistakes before it is too late.

This dynamic is visible in many of the examples already noted. In the case of the Point of Originality tool, for instance, feedback from activities that students are already conducting is routed into the system, and assigned a value that is then passed to the instructor. By monitoring the system, the instructor can observe what material is being emphasized or ignored, and can use that information to further predict which students might be struggling with certain core concepts. The instructor can then choose to go back and reinforce certain concepts or to modify the syllabus accordingly. Should the intervention prove successful, the change will be reflected by the system itself, so that the results of learning analysis are continually fed back to direct student achievement. This is most clearly reflected in the bottom section of Fig. 1, where LA and AA’s respective appeal to varied audiences and actors is modeled.

The top diagram in Fig. 1, marked AA, depicts the transfer of data from students to the institution characteristic of academic analytics. The transfer stops at this point, where the institution acts as both audience and (final) actor. The bottom diagram, marked LA, depicts the transfer of data characteristic of learning analytics. The notable addition, however, is the cycle marked Inset 1. This cycle, from students to an instructor and back again, represents the transfer of data between students and instructors that marks LA’s most novel contribution. Here the instructor becomes an actor, with the ability to take the data generated by LA and to use it to conduct a pedagogical intervention. It is thanks to LA’s enhanced monitoring capabilities that this transfer is permitted to be entirely circular. Possible interventions can be monitored to test their effectiveness, and this feedback in turn is passed along to the instructor. The ostensible black box of students’ classroom activities is continually monitored and improved.

In the part of the diagram marked Inset 2, the same transfer from students to the institution seen in AA is preserved, making clear the way in which an LA implementation (or a series of LA implementations) might be embedded within a broader AA mission. Yet while successful LA implementations might achieve AA goals, it is less clear that a (long-term) AA project will have an immediate impact on classroom performance. Where the early warning system or Point of Originality might clearly reflect one part of the model, just among the test cases already cited, some examples are less clearly demarcated. Moodle, for instance, uses LMS data to suggest course materials that might be more or less popular among students, but the noted use of the system is to tailor the course for future students, not necessarily the students who are contributing the data. As such, the arc between its actors and audience more closely resembles an AA
system than an LA one. Check My Activity (CMA), on the other hand, uses similar information in real-time, but then leaves the intervention component of the implementation entirely to the student’s discretion. In this case, the transfer from actors to audience is not really a transfer, but merely a single, fixed point. This aspect of CMA helps highlight a conundrum shared by even a real-time Moodog-like system. If students are already failing to engage in routine classroom activities, would simple exposure to more course content really improve their progress? Clearly, perusal of all the material related to a course is a prerequisite for acquiring knowledge of the syllabus; that is, after all, why the material is on the syllabus. The black box that represents the acquisition of knowledge remains, in this case, just as opaque as before.

These implementations, while perhaps not fully ideal models of the LA framework are included as examples for what LA might be because they have at least one half of the formula correct. If LA is distinguished from AA by its intended actors and audience, then both Moodog and CMA share one aspect of either. In the case of Moodog, students and teachers are the actors in charge of the tool itself, yet the tool’s benefit is deferred to a different classroom audience sometime in the future. For CMA, the dynamic is reversed; students are the intended audience for reform, but it’s unclear which actors can be responsible for carrying those reforms out. In Fig. 2 above, the sample implementations described in Section IV are sorted by their employment of the numbered strategies for actors and audience noted at the ends of Sections V and VI. Although some implementations only employ a selection of the available trends, it is not necessarily that these implementations in particular are doing anything wrong; rather, it might be suggested that this lingering confusion over the audience and actors dichotomy is a vestige of LA’s roots in academic analytics. Since AA has an established reputation for guaranteeing long-term institutional benefits, it’s almost second nature for a first-generation “LA” tool like Moodog to attempt to do the same thing. Likewise, since many LA tools (like CMA) are built on institutional LMS systems, it’s easy to pass along the data generated by those systems as a worthwhile intervention in and of itself. Yet if LA is to be distinguished as an independent method of analysis, it is important that any claims to assessing learning are supported by practical evidence. This cannot be done by simply targeting future performance or waiting for LMS statistics to pay dividends on their own, with no sense of whether or not the analysis has the capacity to improve present-day learning. Rather, LA’s potential to penetrate the black box of education – LA’s very future – depends upon a stable understanding of the actors and audience at stake.

The danger of AA’s continued influence in the field of learning analytics is that it has the potential to simply replace one conceptual black box with another. The AA model, whereby institutions serve as both the actors and audience for final evaluation omits the actual classroom environment from study entirely. Projections about future classrooms and future students simply replicates the same problems that LA was conceived to avoid. What’s more, because most of the learning and course management systems on which many of these implementations are based tend to be walled off from individual scrutiny, if analytic tools are not placed in the hands of the constituents of the actual classroom, there’s little opportunity for instructors to respond to feedback, to engage with it critically, and to shape it to their needs. Learning analytics offers the opportunity to engage more closely with teaching and learning, yet without a clearly demarcated sense of the relevant stakeholders, and the appropriate audience and actors involved, that opportunity is perhaps even more fleeting than before.

VIII. CONCLUSION

Learning analytics is a burgeoning field of study. Though its roots are found in academic analytics, it differs fundamentally from its forebear in the focus of its actors and its intended audience. This paper examined these conceptual differences and asserted that because of the increased use of academic technology solutions, a “black box” of student learning has developed. Unpacking this box and analyzing its contents depends on the honed focus of learning analytics. By examining a variety of existing tools, similarities were isolated so as to determine the trend in educational tools thus far. This permitted a deeper analysis of the optimal actors and audiences at stake for learning analytics. If learning analytics continues to expand as an innovative and integral part of educational practice, this model of audiences and actors will help ensure that the field is really continuing to target the problems that it was intended to combat.
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Leveraging Existing Data: Indicators of Engagement as Early Predictors of Student Retention

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Abstract—Various measures of student engagement and academic risk were analyzed based on three years of data at Eastern Connecticut State University. Among the data considered was Freshman orientation data collected by the J. Eugene Smith Library. The extent to which the students completed the three parts of the mandatory orientation program was determined to be strongly predictive of retention. Since the Library orientation occurs in the first three weeks of the fall semester for all first-time full time students, the University is now planning to flag students for pro-active advising once their Library orientation completion status is determined. Other data reflecting evidence of student engagement was also analyzed and showed varying degrees of validity as retention predictors.

Keywords—retention; orientation; library; college student persistence

I. INTRODUCTION

Nationally the 6-year college graduation rate for the Fall 2002 cohort at all 4-year institutions was 57.2%. The completion rate for Whites was 60.2%, while only 40.1% of blacks and 48.9% of Latinos from the 2002 cohort finished in six years or less (NCES, 2010). In addition, income gaps exist when looking at who is likely to graduate from college. In 2008, the bachelor’s degree attainment rate by age 24 was 77% for young people from the highest income quartile, but only 10% for their counterparts in the lowest income quartile. The achievement gaps implied in these data represent a substantial waste of institutional and personal resources, and have implications for the nation’s economy. We need to produce more college graduates to compete in the global economy. The United States ranks third among industrialized countries in overall degree attainment but slips to eighth among young adults. The United States will have a college-degree shortfall of 23 million by 2025 (OECD, 2010; Lumina, 2010). One logical approach to this problem is closing the achievement gap that exists between under-represented minority students and low-income students with the remainder of the student population.

Eastern Connecticut State University (ECSU) has been involved in exploiting institutional research data through Project Compass and other initiatives since 2007. Project Compass is the Nellie Mae Foundation’s regional funding initiative for improving retention and graduation rates of minorities, low-income and first-generation students in New England 4-year public colleges/universities. Much of the Project Compass data analysis since the planning year (2007-2008) has focused on identification of first-time full-time (FTFT) students most at risk of not being retained at the start of the second year. Multiple regression models incorporating new student data/Banner data were generated to identify students at risk of not returning for their third semester. These statistical models employed primarily “input” variables (Astin 1993), such as SAT, gender, race, and income (used to determine Pell eligibility). New students were divided into quintiles associated with their predicted retention. Those in the lower two quintiles were earmarked for differentiated treatment (Targeted Advisement). These data analyses to date have concentrated on FTFT cohorts and on retention from first- to second-year.

Administrators at ECSU believed that these statistical techniques had reached a point of diminishing returns. For example, sorting of students into groups by level of risk has not differentiated between students who leave because of academic difficulties and those who transfer successfully. Administrators wished to explore other data-tracking routines that are more actionable (i.e., that provide opportunities to implement student interventions earlier), that allow sorting of students into groups by risk of leaving for academic difficulties versus groups that transfer successfully, and that can reassign risk level based on information gained from behaviors during students’ first year of enrollment. The invitation to participate in the A2S Leading Indicator Project was viewed as an excellent chance to build on this past work and serve as a pilot for the other “Connecticut State University” (CSU) institutions.
II. METHODS

A. Characteristics of Institution and Participants

ECSU is a coeducational, residential public liberal arts university founded in 1889. It is one of four “sister” institutions that comprise the CSU system. Accredited by the New England Association of Schools and Colleges, Inc., Eastern is also a member of the Council of Public Liberal Arts Colleges (COPLAC). It is located in Willimantic, Connecticut, 30 minutes from Hartford. Enrollment for Fall 2010 was 5,606, with 4,416 full-time undergraduates. In terms of the Fall 2010 admissions profile, there were 4,711 applications for full-time admission, with 68% being offered admission. Of those offered admission, 64% were freshmen. The number of new full-time students who actually enrolled was 1,425, with 91% living on campus. Enrolled students had a mean SAT of 1029. Information for the present analyses was obtained about the engagement and academic performance of all first-time-full-time freshmen (N = 2715) who were admitted to the four-year host institution over a three-year period; Fall 2007 Admits (n = 821), Fall 2008 Admits (n = 950), and Fall 2009 Admits (n = 944)

B. Measures

1) Demographic Variables

The pre-existing Project Compass file contained information about the gender, race/ethnicity, and income status of all students. This information was used to determine two demographic variables central to this investigation, status as a “Pell Grant Recipient” (PGR) and status as an “Under-represented Minority Student” (URM). Both variables were dichotomous and scored as “yes” versus “no.” Under-represented minority students included African-American, Hispanic, and American-Indian students. Non-URM students included white and Asian/Pacific Islander students. Students whose race was classified as “unknown” or “other” were excluded from computation of this variable. In addition, the file contained a 10-point rating by admissions personnel of the likelihood for academic success at [institution name removed]. This “Admissions Rating System” uses a 0 – 10 scale (higher scores indicate greater likelihood of success) to evaluate each applicant, as derived from high school class standing (40%), standardized test scores (40%), and subjective factors (20%). Subjective factors include performance in college preparation courses, grade point average, academic rigor of high school, extracurricular activities, demonstration of leadership, life experiences, and a personal interview, when appropriate. This variable was used as an early warning indicator of potential problems in remaining at ECSU.

2) Engagement Variables

Indicators of engagement for the first four semesters were collected from four sources (judicial affairs, housing, student activities, and library orientation) within the university. All indicators represent counts of actual participation in activities as opposed to student report of involvement.

a) Involvement in Judicial Proceedings.

Judicial affairs officials provided a semester-by-semester analysis of the number of offenses in which each student was deemed to be responsible. The judicial officer estimated that roughly 95% of offenses were related to alcohol use (e.g., alcohol in dorm room, underage drinking, etc.).

b) Participation in Community Service Activities.

Housing officials provided the number of community service volunteer activities in which students engaged. This variable was confounded because of a change in University policy in that community service was mandatory for Fall 2007 Admits but was made optional thereafter. The effects of this confound were partially attenuated by creating a “true voluntary community service” variable that melded community service in the second year for the 2007 Admits with first year service for the 2008 and 2009 Admits. This change yielded a more accurate index of volunteerism, but at the expense of losing this information for the first year for students entering in 2007.

c) Membership in Student Clubs.

Student activities officials provided information about the number of clubs each student joined for each of four semesters.

d) Participation in Library Orientation.

Library officials provided information about freshmen participation in a library orientation program. All incoming freshmen are “required” to participate in a three part program: a 30 minute overview PowerPoint presentation by a librarian, a 30-45 minute scripted tour in groups of 20, led by either a librarian or a member of the support staff, and an online information literacy test (TRAILS®). A key element in scheduling the students was the establishment of a course in the University Banner system and registering all incoming freshmen for the course as part of their course registration process. Hence the one-time library session was guaranteed not to conflict with any of their classes and was printed on their course schedule with all their other classes. The Library orientation session is offered during the first three weeks of the fall semester. Students were told during orientation that participation was “mandatory,” but there were no consequences for not participating.

Students could earn points for four possible levels of involvement. Students who attended the live orientation session and completed the online assessment received a 1.5, students who attended orientation only earned 1.0, students who took the on-line assessment but did not attend an

orientation session received 0.5, and students who did not participate received 0.

3) Academic Indicators

For each student, an end-of-semester Grade Point Average (GPA) was computed for each of up to four semesters that students could have been enrolled.

4) Outcome Indicators

Following each semester, the enrollment status of each student was determined by whether that student remained at the college (determined by registering and attending the following semester), did not register, or transferred to another institution as provided by the National Student Clearinghouse Files. This information was used to create a “transfer status” variable that determined whether a student (1) remained at ECSU for two years, (2) dropped out (i.e., failed to enroll over consecutive semesters without enrolling in another institution), (3) stopped-out (i.e., failed to register across consecutive semesters with eventual re-enrollment at the host institution), or transferred to one of five possible types of institutions (4) other “sister” institutions within the CSU system, (5) the major state research university, (6) in-state community colleges, (7) out-of-state community colleges, and (8) other four-year institutions.

C. Concatenating Data Files to Provide Most Accurate Comparisons

Student engagement files contained relatively more data for students from the earlier cohorts. For example, summaries of student engagement variables would necessarily take place over 6, 4, and 2 semesters for 2007 Admits, 2008 Admits, and 2009 Admits, respectively. This bias prevented creation of overall total values across all semesters as the number of clubs joined or judicial offenses would necessarily be larger for students in the earlier cohorts because they would have had more semesters in which to accrue such activities. To remove this bias, all engagement indicators were broken down to provide semester-level (i.e., first semester involvement, second semester involvement, etc.) and year-by-year units. The data file was concatenated so that semester and year units were transposed to match year of admission. This process served to make equivalent across cohorts year-level rates of participation. Only first-year engagement indicators were used to evaluate participation among students in all three cohorts. Finally, these first-year engagement measures were dichotomized to permit pathway analysis of those who participated versus those who did not and also were summed to permit parametric statistical analyses.

III. RESULTS

Data were analyzed to address seven specific issues:

1. describing basic demographic characteristics and engagement indicators of the entire sample;
2. assessing the equivalence of cohorts on demographic and engagement variables;
3. evaluating the interrelationship between URM and Pell status;
4. comparing URM and non-URM students on engagement variables, academic performance, and transfer status;
5. comparing Pell and non-Pell students on engagement variables, academic performance, and transfer status;
6. determining subsequent academic status of students who transferred;
7. examining the utility of ratings of academic risk and library involvement in predicting transfer status.

A. Demographic Features of the Sample

In terms of basic demographic features (Table 1), the student sample was predominantly white (80.4%); with 53.1% being women, and 20.1% and 15.0% being Pell recipients or URM, respectively. A majority of the students (68.8%) remained at the host institution for their first two years of enrollment, with 12.5% enrolling in other four-year colleges [including sister schools] (3.6%), the state research institution (4.3%) or other four-year institutions (4.6%), 9.6% enrolling in either in-state (7.8%) or out-of-state (1.8%) community colleges, and 8.4% dropping out or stopping out (0.6%).
Table 1: Demographic Characteristics of the Sample.

<table>
<thead>
<tr>
<th>RACE/ETHNICITY</th>
<th>FREQUENCY</th>
<th>PRECENT</th>
</tr>
</thead>
<tbody>
<tr>
<td>ASIAN/PACIFIC ISLANDER</td>
<td>47</td>
<td>1.7</td>
</tr>
<tr>
<td>BLACK</td>
<td>195</td>
<td>7.2</td>
</tr>
<tr>
<td>HISPANIC/PUERTO RICAN</td>
<td>189</td>
<td>7.0</td>
</tr>
<tr>
<td>MIXED ETHNICITY</td>
<td>17</td>
<td>.6</td>
</tr>
<tr>
<td>NATIVE AMERICAN</td>
<td>24</td>
<td>.9</td>
</tr>
<tr>
<td>OTHER</td>
<td>7</td>
<td>.3</td>
</tr>
<tr>
<td>UNKNOWN</td>
<td>54</td>
<td>2.0</td>
</tr>
<tr>
<td>WHITE</td>
<td>2182</td>
<td>80.4</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>GENDER</th>
<th>MEN</th>
<th>1274</th>
<th>46.9</th>
</tr>
</thead>
<tbody>
<tr>
<td>PELL RECIPIENTS</td>
<td>547</td>
<td>20.1</td>
<td></td>
</tr>
<tr>
<td>URM</td>
<td>408</td>
<td>15.0*</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>TRANSFER STATUS</th>
<th>REMAIN</th>
<th>1868</th>
<th>68.8</th>
</tr>
</thead>
<tbody>
<tr>
<td>DROP OUT</td>
<td>229</td>
<td>8.4</td>
<td></td>
</tr>
<tr>
<td>STOP-OUT</td>
<td>17</td>
<td>0.6</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>TRANSFER TO: OTHER CSU SCHOOL</th>
<th>97</th>
<th>3.6</th>
</tr>
</thead>
<tbody>
<tr>
<td>STATE RESEARCH INSTITUTION</td>
<td>116</td>
<td>4.3</td>
</tr>
<tr>
<td>Other Four-Year Institutions</td>
<td>126</td>
<td>4.6</td>
</tr>
</tbody>
</table>

| IN-STATE COMMUNITY COLLEGE     | 212       | 7.8     |
| OUT-OF-STATE COMMUNITY COLLEGE| 50        | 1.8     |

*78 students we excluded from this analysis because the definition of URM excludes “Other” and “Unknown” ethnicities.

Table 2 contains scalar information about the ranges, averages, and standard deviations of engagement and academic performance variables. Absence of an engagement indicator was scored as 0, which had the effect of lowering mean engagement scores because overall rates of participation were low. Of the 2715 students, 694 (25.6%) had judicial offenses, 653 (24.1%) engaged in community service activities, and 829 (30.5%) were members of clubs during their first year.

Table 2: Ranges, Means, and Standard Deviations of Engagement and Academic Performance Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Admissions Rating</td>
<td>1</td>
<td>10</td>
<td>5.97</td>
<td>2.02</td>
</tr>
<tr>
<td>Total Offenses Year 1</td>
<td>0</td>
<td>5</td>
<td>0.34</td>
<td>0.67</td>
</tr>
<tr>
<td>Community Service Year 1</td>
<td>0</td>
<td>7</td>
<td>0.39</td>
<td>0.86</td>
</tr>
<tr>
<td>Total Club Memberships Year 1</td>
<td>0</td>
<td>16</td>
<td>0.69</td>
<td>1.31</td>
</tr>
<tr>
<td>Total Leadership Positions Year 1</td>
<td>0</td>
<td>4</td>
<td>0.07</td>
<td>0.37</td>
</tr>
<tr>
<td>Extent of Library Training</td>
<td>0.00</td>
<td>1.50</td>
<td>1.07</td>
<td>0.54</td>
</tr>
<tr>
<td>GPA First Semester</td>
<td>0.00</td>
<td>4.00</td>
<td>2.73</td>
<td>0.92</td>
</tr>
<tr>
<td>Hours Earned First Semester</td>
<td>0</td>
<td>19</td>
<td>13.28</td>
<td>3.76</td>
</tr>
<tr>
<td>GPA Second Semester</td>
<td>0.00</td>
<td>4.00</td>
<td>2.79</td>
<td>0.93</td>
</tr>
<tr>
<td>Hours Earned Second Semester</td>
<td>0</td>
<td>20</td>
<td>13.53</td>
<td>3.81</td>
</tr>
<tr>
<td>GPA Third Semester</td>
<td>0.00</td>
<td>4.00</td>
<td>2.80</td>
<td>0.89</td>
</tr>
<tr>
<td>Hours Earned Third Semester</td>
<td>0</td>
<td>19</td>
<td>13.90</td>
<td>3.15</td>
</tr>
<tr>
<td>GPA Fourth Semester</td>
<td>0.00</td>
<td>4.00</td>
<td>2.85</td>
<td>0.86</td>
</tr>
<tr>
<td>Hours Earned Fourth Semester</td>
<td>0</td>
<td>19</td>
<td>13.51</td>
<td>3.56</td>
</tr>
</tbody>
</table>
B. Equivalence of Cohorts across Time

Cross-tabulations were computed to determine whether admit year cohort was differentially related to demographic features. Chi-square analyses indicated that members of the three cohorts were equivalent in terms of gender, percentage of Pell recipients, URM students, and first transfer status.

Analysis of variance on academic indicators revealed a significant, $F(2,2706) = 3.85, p < .05$, improvement in first-semester GPA ($M = 2.66, 2.73, 2.78$ for the 2007, 2008, and 2009 Admits, respectively) as well as significant, $F(2,2706) = 9.63, p < .001$, improvement in number of first-semester academic credits earned ($M = 12.88, 13.26,$ and 13.67) for the 2007, 2008, and 2009 Admits, respectively. Analysis of second semester academic data generally revealed similar significant outcomes, with 2007 Admits performing less well than students in the other two cohorts.

Analysis of variance on engagement indicators revealed a significant, $F(2,2712) = 24.71, p < .001$, linear decline in judicial offenses ($M = 0.43, 0.39, 0.22$ offenses for the 2007, 2008, and 2009 Admits, respectively). Membership in clubs was significantly higher, $F(2,2712) = 13.59, p < .001$, in the two later cohorts ($M = 0.77$ and 0.78 for 2008, and 2009 Admits, respectively) compared to the 2007 Admits ($M = 0.42$). Number of first-year leadership positions manifested a significant increase ($M = .05, .07, .09$ positions over the three respective cohorts). Because this increase involved only a very small percentage of enrolled students (only 4% occupied leadership positions in their first year), number of leadership positions was not used in further analyses. Extent of library training showed a significant, $F(2,2712) = 66.85, p < .001$, linear decline across cohorts ($M = 1.21, 1.11,$ and 0.91 for the 2007, 2008, and 2009 Admits, respectively). This decline may be attributed to the fact that the Library more aggressively pursued follow-up on the “mandatory” orientation in the early years of the program and became less rigorous in following up in subsequent years.

C. Overlap Between Members of URM and Pell-Status Students

Cross-tabulation and chi-square analysis of categorization of URM and Pell status revealed a moderate (but highly significant overlap, $\chi^2(1) = 158.24$) between the two groups; 43.4% of the URM students received Pell support and 33.1% of all Pell recipients were URM students). This interrelationship implies that outcomes from analyses involving the two categories will overlap to some extent.

D. Pathway Analyses of Student Characteristics, Activities, and Transfer Status

Figure 1 (Appendix) provides a longitudinal analysis of educational outcomes and also displays characteristics of the subsamples of students who remained versus those who dropped out. Drop-outs were slightly more likely to be Pell recipients or URM students, to have more judicial infractions, and less likely to be members of clubs or to engage in volunteer activities. In addition, drop-outs were less likely to engage in (or complete) library training and to earn GPAs above 2.0 in both their first and second semesters.

E. Engagement as a Function of URM and Pell Status

Additional information about the relative effects of the engagement variables was gleaned through application of multivariate analyses. Differential engagement as a function of URM and Pell status was evaluated via multivariate analyses of covariance. For these analyses, transfer status was trimmed to compare students who remained for two years versus those who dropped out. The 2 X 2 design contrasted URM versus non-URM students and students who remained versus drop-outs, with SAT verbal and mathematics scores serving as covariates. Mean scores for engagement variables for URM and Pell students are presented in Tables 3 and 4, respectively.

A significant main effect emerged for URM status, multivariate $F(4,1835) = 2.68, p < .05, \eta^2 = .006$. This overall effect was carried by significant differences in 2 of the 4 dependent measures, such that URM students were members of significantly more clubs, $F(1,1838) = 5.01, p < .05, \eta^2 = .003$, but engaged in significantly less extensive library training, $F(1,1838) = 4.58, p < .05, \eta^2 = .002$.

A significant main effect also emerged for transfer status, multivariate $F(4,1835) = 6.19, p < .05, \eta^2 = .013$. This overall effect was carried by significant differences in 3 of the 4 dependent measures, such that drop-outs were members of significantly fewer clubs, $F(1,1838) = 12.75, p < .001, \eta^2 = .007$, engaged in less community service, $F(1,1838) = 6.24, p < .051, \eta^2 = .003$, and, again, engaged in significantly less extensive library training, $F(1,1838) = 8.72, p < .01, \eta^2 = .005$. Neither the multivariate nor any univariate F-value was significant for the interaction between URM and transfer status.

Table 3: Means of First-Year Engagement Variables by URM and Dichotomized Transfer Status

<table>
<thead>
<tr>
<th></th>
<th>Non-URM Students</th>
<th>URM Students</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Transfer Status</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Drop-Out</td>
<td>Remain</td>
</tr>
<tr>
<td>Total Offenses</td>
<td>0.42</td>
<td>0.34</td>
</tr>
<tr>
<td>Community Service</td>
<td>0.26</td>
<td>0.44</td>
</tr>
<tr>
<td>Total Club Members</td>
<td>0.21</td>
<td>0.67</td>
</tr>
<tr>
<td>Extent of Library Trng.</td>
<td>0.91</td>
<td>1.12</td>
</tr>
</tbody>
</table>
Results for the analysis examining Pell status were different than those obtained for the URM comparison. Pell status did not yield a significant multivariate main effect or significant differences on any of the single dependent engagement variables. Interaction effects were also not significant, but, as would be expected, transfer status yielded outcomes similar to those just described.

**Table 4: Means of First-Year Engagement Variables by Pell and Dichotomized Transfer Students**

<table>
<thead>
<tr>
<th>Pell Status</th>
<th>Non-Pell Students</th>
<th>Pell Students</th>
</tr>
</thead>
<tbody>
<tr>
<td>Transfer Status</td>
<td>Drop-Out</td>
<td>Remain</td>
</tr>
<tr>
<td>Total Responsible Offenses</td>
<td>0.48</td>
<td>0.33</td>
</tr>
<tr>
<td>Volunteer Community Service</td>
<td>0.26</td>
<td>0.44</td>
</tr>
<tr>
<td>Total Club Memberships</td>
<td>0.23</td>
<td>0.69</td>
</tr>
<tr>
<td>Extent of Library Training</td>
<td>0.92</td>
<td>1.11</td>
</tr>
</tbody>
</table>

These outcomes suggest that students who ultimately drop out are considerably less engaged in opportunities offered in the first year. Extent of library training appears to be an excellent early indicator of engagement and the likelihood of remaining on campus over the first two years as this variable also correlated positively with number of clubs joined, \( r = .08, p < .001 \), and negatively with number of judicial offenses, \( r = -.13, p < .001 \), in the first year. In addition, failure to complete training in how to use library resources appears to have particularly deleterious academic consequences as this measure is predictive of GPA in the first, \( r = .26, p < .001 \), and second, \( r = .24, p < .001 \), semesters.

Figure 2 (Appendix) describes cohort data for the 601 students who transferred to a sister CSU School, the major state research university, another four-year college, or to a community college. The major differences between students transferring to four-year institutions and community colleges are found in higher first- and second-semester GPAs and greater completion of library training, all favoring the former. Students transferring to the state research institution were less likely to be active in clubs and those transferring to out-of-state community colleges were more likely to have accrued judicial infractions. Of these 50 transfers to out-of-state community colleges, 42 (84%) had been accepted originally from out-of-state locations.

**F. Summary of Transfer Students’ Subsequent Academic Enrollments**

Additional analyses examined subsequent enrollments of the 601 transfer students. These analyses revealed that a large majority of transfer students stayed at the institutions to which they transferred initially. Of 97 students who transferred to a sister CSU institution, 89 remained at the institution to which they transferred, 4 dropped out (i.e., did not complete subsequent semesters and did not enroll in another institution), 2 transferred to a community college, and 2 transferred to another 4-year institution. Of 116 students who transferred to the state research university, 110 remained (i.e., showed enrollment over all applicable semesters), 3 dropped out, 2 transferred to a community college, and 1 transferred to another 4-year institution. Of 126 students who transferred to four-year institutions, 116 remained, 9 appeared to drop out), and 1 transferred to an in-state community college.

Interpreting outcomes for students who transferred to in-state and out-of-state community colleges was problematic for several reasons. Because students transferred between their second and fourth semesters, it is impossible to differentiate students who completed the associate degree versus those who dropped out entirely. In addition, a number of students “stopped out” for a semester. Finally, we could not be certain of the subsequent status of students who did not transfer until the fourth semester. We, therefore, counted students as remaining at in-state community colleges only if they were enrolled for at least two consecutive semesters. Those who transferred in the 4th semester were labeled as providing “no further data.”

Of 212 students who transferred to in-state community colleges, we could account for 151 with reasonable accuracy. Of the 151, 97 remained for two or more consecutive semesters, 41 showed “no further data,” 4 transferred to a sister CSU institution, 1 transferred to the state research university, and 8 transferred to another 4-year institution. Of 50 students who transferred to out-of-state community colleges, 36 remained, 10 showed “no further data,” and 4 transferred to a 4-year institution. Although this analysis is based on only 4 semesters of transfer data and, therefore, provides only a short-term glimpse of student movement, our best estimate is that, across the transfer categories into four-year institutions, 92.9% remained at the institution to which they initially transferred. Estimated retention rates were 94.8% at the state research institution, 92.1% at other four-year institutions, and 91.7% at sister CSU schools. The best estimates of subsequent retention were 64.2% and 72.0% for in-state and out-of-state community colleges, respectively. Given our method of computation, these two latter figures are likely to be artificially low.
G. Predictive Utility of Admission Ratings and Library Involvement

One final analysis evaluated the predictive utility of admissions ratings in combination with library involvement in predicting whether students remained at ECSU or dropped out during the first two years. This analysis dichotomized administrator ratings (≤ 5 versus >5), then crossed those two categories with extent of library training and with drop-out status. Results of this analysis are presented in Table 5.

Table 5: Percentages of Students Who Dropped Out as a Function of Admission Ratings and Extent of Library Training

<table>
<thead>
<tr>
<th>ADMISSION RATING</th>
<th>BELOW OR EQUAL 5</th>
<th>ABOVE 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>NO LIBRARY TRAININGS</td>
<td>18.9</td>
<td>13.1</td>
</tr>
<tr>
<td>ON-LINE ASSESSMENT ONLY</td>
<td>20.5</td>
<td>14.3</td>
</tr>
<tr>
<td>LIVE TRAINING INVOLVEMENT</td>
<td>10.3</td>
<td>7.5</td>
</tr>
<tr>
<td>BOTH ON-LINE ASSESSMENT AND LIVE TRAINING</td>
<td>8.2</td>
<td>6.7</td>
</tr>
</tbody>
</table>

These percentages indicate that students who either did not take the library training or who took only the on-line assessment were almost twice as likely to drop out as students who actually attended a live session (or live session plus on-line assessment). This two-fold difference was similar for students at both high and low academic risk, as judged by admissions counselors. Attending a live training session, however, seemed to attenuate the risk of dropping out, especially for students initially judged to be at higher academic risk. Identical cross-tabulations were computed for URM students and Pell Recipients only. The smaller sample sizes changed the percentages somewhat, but the overall pattern remained similar, with URM and Pell Recipient students with low admission ratings who do not engage in the library training appearing to be at most risk.

H. Comparing Students Who Remained at a 4-Year Institution vs. Drop-outs or CC Transfers

To more precisely parse the behaviors associated with academic persistence, a stepwise Discriminate Function Analysis (DFA) was used to categorize membership in one of two groups. A dichotomous variable was created contrasting students who remained at a 4-year institution VS those who dropped out or moved to a community college. Stepwise DFA determines which predictor variable is most influential in determining group membership, then the second most influential predictor, and so on. At each step, DFA tests the statistical significance of each predictor. For this analysis, three predictor variables were employed: (a) extent of library training; (b) number of clubs joined during the first year; and (c) number of judicial offenses during the first year. This analysis revealed that extent of library training was the most powerful discriminating variable, \( F(1, 2405) = 43.55, p < .001 \), followed by number of clubs joined, \( F(2, 2405) = 34.13, p < .001 \). Number of judicial offenses in the first year was not a statistically reliable predictor.

I. Relevance for Learning Analytics

Regression and discriminant function prediction analyses employed within major theoretical models of student retention and persistence (Astin, 1968, 1993; Pascarella, 1985; Tinto, 1975, 1987) typically account for 20% to 30% of the variance (Kennedy, Sheckley, & Kehrhan, 2000; Kohen, Nestel & Karmas, 1978; Muuter, 1992). In the Kennedy et al. investigation, for example, discriminant function analysis on the basis of social and academic adaptation accounted for 29% of the variance and led to the correct classification of 88% of the persisters but only 55% of the non-persisters. Kennedy et al. suggested that the decision to remain in college results from “dynamic interactions and are not due to the linear one-to-one paths depicted in many models of persistence” (p. 11). The predictors explored in this investigation (library training, club participation, and judicial offenses) attempted to expand both (a) the array of variables related to social readiness and/or maturity for college that are available to predict student success and retention; and (b) amount of explained variance.

IV. DISCUSSION

Reason, Terenzini, and Domingo (2006) identified the first two years as the greatest period of college student growth. Students reportedly make 80% to 95% of their total gains in English, mathematics, and critical thinking skills during this period. This investigation employed behavioral indicators of involvement during students’ first year of college to predict subsequent academic and transfer outcomes. Aggregated across three cohort years, 31.2% of entering freshmen left [institution name removed] before completing two years. A majority (71%) of these students who left, however, appeared to continue their education elsewhere. A majority (56%) of transfers were admitted to other four year institutions whereas 44% entered community colleges.

Less than 9% of the students actually dropped out. Important differences emerged, however, when comparing students who remained versus those who dropped out. Compared to students who remained for two years, students who dropped out were slightly more likely to be Pell recipients or URM students, to have more judicial infractions, and were less likely to be members of clubs or to engage in volunteer activities. Active engagement in clubs and other extracurricular activities promotes interdependence and clarity of purpose among students (Foubert & Grainger, 2006). In
addition, drop-outs were less likely to earn GPAs above 2.0 in both their first and second semesters. Greater likelihood of dropping out was predicted by a combination of admission ratings that suggested less success and failure by FTFT students to actually attend a “mandatory” session of training in how to use the University library. Students who did not take the training or who took only the online assessment were almost twice as likely to drop out as students who attended a live session, regardless of level of academic risk.

A. Suggestions for Intervention

Entering college is can be a confusing transition for many students, especially those who have no familial familiarity with the college experience (Astin, 1993; Pike & Kuh, 2005). Confusion can be heightened because most universities encompass two somewhat incompatible enculturation models (Ponce, Williams, & Allen, 2005). Many faculty members subscribe to a mastery model which assumes that students have the necessary skills to be academically successful, need little support, and profit from periodic summative evaluations (e.g., examinations). Student affairs support personnel tend to subscribe to a mentoring model that emphasizes wider arrays of interpersonal contact between more- and less-expert individuals, greater sharing of resources, heightened advocacy, and more frequent use of formative feedback.

There is evidence the mentoring experiences are modestly but consistently (Allen, Eby, Poteet, Lentz, & Lima, 2004) associated with greater success. Despite such positive outcomes, mentoring is not offered widely because of fiscal or time constraints. This investigation suggests that students who are judged to be at risk by admissions personnel be identified as possible candidates for mentoring. Actual mentoring resources could then be directed more specifically toward students who do not engage early and personally in academically helpful training activities, such as education about how to use library resources. Within a wider time frame, students who fail to earn a GPA of 2.0 at the end of the first semester could also be targeted.

B. Weaknesses of the Investigation and Suggestions for Future Assessment

A major weakness of this investigation resides in the analysis of incomplete and truncated data within a changing context of University regulations. As one example, assessment of community service during students’ first year was confounded by a regulatory change that made such service non-mandatory for latter two of the three cohorts.

Housing, student activities, and judicial affairs administrators are implementing sophisticated and complex databases to track activities of students. The judicial database contains information about the number, type and severity of offenses, sanction levied, and if and when sanctions were completed and removed. The housing database melds information about students’ volunteer activities and attendance at educational meetings offered within dormitories. The student activities database tracks club memberships, types of clubs, and leadership positions occupied. All of these data sources are in the early phases of development. Growth in their sophistication and potential utility in predicting student outcomes currently depends on the active involvement of these administrators, who are fully engaged with other, more central activities.

The search for new variables was focused on finding indicators that may provide a higher level of precision in identifying students at risk of not persisting in college. In addition, the search was looking for indicators that would emerge relatively early in students’ initial enrollments, so that intervention strategies could be used early enough to affect positive change. Library training is offered to all new enrollees early in the first semester, so serves an excellent indicator. Club participation provides good predictive value of persistence, however the incidence of involvement in clubs is low, so it is less practical to use as an indicator.

REFERENCES


Identifying Places for Pedagogical Intervention: A Use Case of the “Point of Originality” Tool

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Abstract—This paper describes a tool and method for the objective evaluation of student work through the identification of original content in writing assignments. The tool allows instructors to track how key phrases are employed and evolve over the course of a student’s writing, and to automatically visualize the point at which the student’s language first demonstrates original thought, phrased in their own, original words. Earlier evidence shows that the tool can be predictive of students’ writing in a manner that correlates with their progress in the course and engagement in the technology-mediated activity. This paper presents a plausible use case scenario for how the values generated by the tool could be used by an instructor to preemptively identify likely success or failure, and defines the terms on which pedagogical interventions would be grounded.

Keywords—learning analytics; pedagogical monitoring; recasting; iterative activities

I. INTRODUCTION

For most if not all learning activities, a substantial amount of an instructor's time and effort is devoted to evaluating and monitoring the quality of students' work, and thus, hopefully, the depth and breadth of their learning [5]. The purpose of this monitoring, however, is not merely the determination of grades; part of the instructor's work is entirely self-reflective, enabling the instructor to concurrently, or ideally even preemptively, intervene to make adjustments to course pedagogy based on students' engagement or understanding [6]. While assigning grades might be facile, some difficulties complicate this second objective. If students are only ever tested at fixed intervals – during midterm or finals periods, for instance – then how might an instructor intuit when, precisely, students have understood the material sufficiently? How can an instructor best determine whether or not students are on track?

One possible means of addressing these problems has been found in the increased reliance on iterative writing assignments like co-blogging (see e.g. [1]), response papers, or other activities that allow students to reflect on course material at more regular intervals [47]. These iterative exercises should also allow instructors more opportunities to reflect on students’ collective and individual progress. Yet especially with the concurrent trend towards larger (or so-called “gateway”) courses [2], doing so can be an intensely laborious and time-consuming process, far more complicated than the simple reading and re-reading of any single student’s work. A student’s understanding of a single concept one week needs to be compared to his or her work in prior weeks, and this in turn compared to the work of every other student for every other concept or topic that the course might conceivably cover.

When supporting learning using technology, however, a positive by-product is that students produce their work in an electronic form, which enables the creation of computer-assisted instructional aids [7]. This paper describes an automated solution that can be used by educators to help resolve these tensions. Through the application of lexical analysis to student writing, we have implemented an analysis tool that allows an instructor to track how a student's written language migrates from mere paraphrase to mastery, isolating the moment when the student's understanding of core concepts best demonstrates an ability to place that concept into his or her own words, a moment that we've chosen to call the “point of originality.” This process recreates the same cognitive activity that educators might ordinarily undergo, yet in an automatic manner that is less labor-intensive. Ultimately, the resulting data is presented to the instructor by way of a custom visualization, which allows for continuous self-monitoring with minimally expended effort.

The Point of Originality tool has already demonstrated its potential to provide strong predictors of student outcomes [48]. The average values produced by the Point of Originality tool for iterative assignments have a proven correlation with students’ final (summative) grades on the same material [48]. This paper seeks to build upon these results to provide a viable use case scenario for how an instructor might deploy the tool to isolate likely struggling or successful students while a course is actually in progress.

The paper is organized as follows. Section II explores the difficulties for higher order thinking specifically endemic in larger classes in higher education. Sections III models co-blogging as a possible iterative activity capable of resolving some of these difficulties. Sections IV and V introduce the Point of Originality tool, discussing both its underlying theoretical and pedagogical principles as well as the specifics of its analysis method. Section VI discusses two modifications to the point of originality algorithm aimed at mitigating two possible scenarios likely to produce false positive results.

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Section VII summarizes earlier findings gathered using the point of originality method. The heart of the paper, Section VIII, then provides a possible use case for how an instructor could imply the tool to define possible points of individual or collective pedagogical intervention. The paper concludes by discussing future work.

II. PROBLEMS WITH LARGE CLASSES AND THE NEED FOR PEDAGOGICAL MONITORING

The ability to monitor and respond to student progress is ever more imperative given the realities of the modern classroom. As noted even a decade ago, the political economies of American universities increasingly mandate large class sizes, particularly in the introductory or “gateway” courses that are typically a student's first exposure to collegiate work [2]. These large classes have a negative impact on students and instructors alike. There is, for example, an abidingly inverse correlation between class size and student achievement [25], [26]. The large lecture, while useful for reinforcing rote facts, is less successful in fostering higher-order thinking [3], [4], or in encouraging students to construct their own understanding of core concepts [2]. Such a sizable student population further constrains instructors' abilities to familiarize themselves with students' individual learning styles [2], thereby forcing instructors to assume that their audience consists of uniform types of learners [4]. Although the extent of feedback that students receive is one of the most powerful predictors of student achievement [27], [28], instructor feedback in large lecture courses is often slow and sporadic; students typically need to wait weeks – from, for example, one midterm assessment to the next – to put their course-related skills into practice, and even longer than that to have their assignments evaluated by an instructor [4]. Pedagogical adjustments, in other words, become both more unwieldy and more unlikely in the precise environment where they would be most necessary.

Given the problems inherent to large lecture classes, but given also their entrenched status within the American university system, it would thus logically be prudent to find a way to minimize their most pernicious consequences. Any broader attempt to remedy the problems of larger gateway courses should thus aspire to foster higher-order thinking while providing students with feedback as rapidly as possible. Rather than waiting for the next midterm assignment, regular iterative exercises provide an opportunity for students to participate more freely and more frequently, and an opportunity for instructors to provide earlier feedback. Although educational activities, like the one discussed in the following section, can be designed to address this first objective, allowing instructors to systematically locate where and why feedback is even necessary is the express purpose of the Point of Originality tool.

III. CO-BLOGGING AS ITERATIVE EXERCISE

Co-blogging is an example of an iterative social computing activity that can be very conducive to learning [8], [1]. Overall, blogging provides a platform that promotes individual expression, enables students to establish their own “voice” and yields a richer conversational interactivity within a community [9], [10]. Each student has a blog, composed of multiple blog posts. Students can read each other's blog posts and comment on them. Because blogs are easy to use, they can promote students' digital fluency [11] and encourage students to explore and publish their own nascent ideas under less pressure than in the rough-and-tumble of in-class discussions [12].

Writing a blog forces students to become analytic and critical as they contemplate how their ideas may be perceived by others [10]. Being able to review older contributions affords reflection and enables students to revisit and revise their artifacts, further developing their own viewpoints in the context of each other's writing as they sense how others understand the material similarly or differently [13]. Conversations emerge when students read, and then comment on, each other's blog posts, thus enabling them to exchange, explore, and present alternate viewpoints on the course material [14]. This type of social explanatory discussion can benefit learning [15], [16].

Overall, having students discuss and/or “argue” about course readings has significant educational utility [22], [23], [24]. Some discussion might take place during class, however, class time is a limited resource. A blogosphere can function as a repository of information, opinions, monologues and dialogues about course content, where students participate, and leverage each other's contributions in other educational activities, for instance, when writing term papers [19], [20]. Co-blogging thus constitutes an ideal iterative activity, allowing students to express ideas outside of the confines of the classroom, and to put their thought onto paper prior to summative evaluation.

IV. DEFINING “ORIGINALITY” IN STUDENT WRITING

When students engage in a writing activity, the final evaluation of their work cannot only assess whether or not the student has provided the most closely correct answer. Process is just as relevant to student writing as content [34]. Student writing that exhibits exceptional higher-order thinking is generally seen as that which demonstrates a mastery of the course material in new, profound or statistically unusual ways [35]. The ideal is not only for students to confirm that they've understood lectures, but to do so in ways that even the educator might not have thought of.

This process of mastery need not take place all at once. As a student is continually exposed to the same material, or is given the independent opportunity to rethink, reframe, or revisit that material [36], their writing on the subject has the chance to evolve, from rote regurgitation to wholly original expression [37]. At the level of language, this evolution is reflected through recasting.

Recasting is the learning process whereby a student refines his or her understanding of a concept found in course lectures or readings by putting that concept into his or her own words [38]. In the acquisition of new languages especially, this process can be useful, because it allows students to acquire new vocabulary using the assortment of words already available to them [38], [39]. Even where the student's understanding of a language is not an explicit concern, recasting can mark a student's attempts to graduate to more sophisticated or professionalized terminology, or, inversely but to the same end,
to place new concepts into terms that are nearer to what the student would naturally be more likely to say [40]. “Originality,” fully defined, can of course take numerous forms. The concept of recasting, however, spans a number of theoretical orientations, with an influence on theories of schema formulation [41], the sensemaking process known as “scaffolding” [42], as well as the express principles of educational constructivism [43].

For an instructor, the simple identification of recast terminology within a student's written work can provide an effective barometer for pedagogical self-reflection. If a subset of terms or concepts are deemed vital to the syllabus, repetitions and recast iterations of those same terms will at least suggest that those terms are being acknowledged and reflected upon. Although the presence of recast terminology is not the only metric representative of a student's mastery, the central role that recasting plays in a host of pedagogies (e.g. [41], [42], [43]) suggests that writing demonstrating high or low levels of originality is a point of originality within student writing.

V. EVALUATION OF ORIGINALITY IN CO-BLOGGING

The process of computer-assisted evaluation of student writing is primarily composed of two parts: the analysis method, and a custom-made visualization depicting each student's “originality” at any given time throughout the duration of the semester.

A. Analysis Method: Theoretical Background

WordNet is a lexical database that arranges nouns, verbs, adjectives, and adverbs by their conceptual-semantic and lexical relationships [44]. It might be thought of as a kind of hierarchical thesaurus; whereas a simple thesaurus would be able to identify any two words as synonyms or antonyms of one another, WordNet is able to note the similarity between two words that don't have literally identical meanings. These relationships are ideally meant to mirror the same lexical associations made by human cognition.

WordNet's hierarchical arrangement means that certain terms are more closely related than others. Within WordNet, these relationships are displayed as “synsets,” clusters of terms that fork, like neurons or tree branches, from more specific to more and more diffuse associations (see Figure 1). If two words are found within one another's synset tree, it stands to reason that these terms are, in some way, related, be it closely or distantly. As discussed in the next sub-section, these distances between two terms can be calculated, and assigned a value commensurate with their degree of semantic relatedness [45].

The hierarchical arrangement inherent to WordNet provides one method of determining the relationship between two terms. If the synset tree of one term encompasses another term, it is simple enough to note how many synset jumps it takes to move from one to another. In Figure 1, a “Dalmatian” is a type of “dog,” which itself belongs to the subcategory of “domestic animals;” thus there are two tiers of associations between the concepts of “Dalmation” and “domestic animals.” Unfortunately, however, just how closely any two terms might be related is not a purely linear relationship. WordNet organizes related terms by their precise lexical entailment, such that nouns might be categorized as synonyms, hypernyms, hyponyms, holonyms and meronyms, as seen in Table 1.

These possible entailments provide a rudimentary roadmap for all the ways in which two words might be related. Since WordNet attempts to map the cognitive associations automatically formed between words [44], a student's evocation [46] of the holonym or hypernym of a given noun instead of the noun itself is more likely to form an associative recast of the original term.

Yet while this simple index displays just how any two terms might be related, all the possible relationships noted are not necessarily equal. Some relationships, like that between synonyms smile and grin, are obviously bound to be more strongly associated than that between mammal and dog. Following a method first noted by Yang & Powers [49], it is possible to install a series of weights that can best calculate the semantic distance between any two terms. This method in particular is useful because of all known methods, it bears the highest correspondence between its own distance calculations and the intuitions of actual human respondents (at 92.1 percent accuracy).

<table>
<thead>
<tr>
<th>Synonym: X is a synonym of Y if X means Y</th>
<th>Example: {smile, grin}</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hypernym: X is a hypernym of Y if every X is a kind of Y</td>
<td>Example: {dog, mammal}</td>
</tr>
<tr>
<td>Hyponym: X is a hyponym of Y if every Y is a kind of X</td>
<td>Example: {mammal, dog}</td>
</tr>
<tr>
<td>Holonym: X is a holonym of Y if Y is part of X</td>
<td>Example: {hand, finger}</td>
</tr>
<tr>
<td>Meronym: X is a meronym of Y if X is part of Y</td>
<td>Example: {finger, hand}</td>
</tr>
</tbody>
</table>

Table 1. Possible Lexical Entailments in WordNet

B. Analysis Method: Implementation

To determine the point of originality for a student’s blog post, an instructor need only manually input a specific set of query terms based on any number of key course topics or
concepts. These query terms are the starting place for analysis: for each query term, the tool generates a WordNet synset tree. Words within the tree are then compared to the body of words extracted from a student's blog post. For any “synset match,” the tool then performs the kind of “distance calculation” characterized above [47].

We can think of these matching terms as being connected by a new “tree” in their own right, based on their particular lexical entailment – for instance, the hypernym/hyponym relation given in Figure 1. The distance between any two terms is given as a numerical expression based on the type of lexical entailment (as given by [49] and modeled by [47]) and the number of “tiers” of association separating one term from another. In Figure 1 above, the term “Dog” is separated from its parent category of “Domestic animal” by one tier. “Cat” in turn is a child category of “Domestic animal.” Thus a distance calculation for these two terms would note the shared parent; only one term separates “Cat” from “Dog.” If we can extend this admittedly rudimentary example to a hypothetical (and no doubt remedial) course in Zoology whereby an instructor wanted to track student expression of the basic concept “Animal,” he would simply enter this concept as a query term. In return, the Point of Originality tool would be able to identify both “Dog” and “Cat” and “Dalmation” (and manifold other words) as recast iterations of the concept of “Animal.” A more practical exploration of this same dynamic will be discussed in Section VIII.

The distance calculations for all synset matches for a student’s blog post are then summed. The resulting total is the numeric expression of that post’s point of originality for the particular query terms. This process is repeated for each interval in the student’s iterative activity, with the results then plotted on a horizontal timeline. Although this paper focuses on the analysis of blog posts as students’ writing examples, given some additional programming work, any electronic form of student writing could be made compatible with the tool for subsequent analysis.

C. Visualization of the Point of Originality

The timeline visualization for the Point of Originality tool allows for an optimal instruction comprehension whereas the instructor can see recasts of a particular course topic across the entire body of a student's writing throughout a single course. The visualization, as seen in Figure 2, displays a horizontal timeline that represents the time interval for the writing activity of any student for the duration of a particular semester. The numbered components of Figure 2 correspond to the following features.

1) This drop-down menu allows the instructor to select which students writing samples are currently being displayed.

2) This is where query terms (Q) are input by the instructor.

3) This timeline displays the date/times of each of the students writing samples. Each marker is color-coded, from colder to warmer colors along the ROYGBIV spectrum, the higher the value of the point of originality (P) score for any given writing sample. These color assignments present an intuitive way for the instructor to quickly recognize that the sample has been assigned a higher originality value.

4) If a writing sample marker is selected in the timeline window (see Inset 3), the text of that writing sample is displayed here. This assortment of visualization options allows the point of originality calculation to be displayed in a number of intuitive ways: both within chronology (Inset 3) and in context (Inset 5).

VI. Decay and Distance: Adjustments to the Point of Originality Algorithm

An evaluation of the efficacy of the point of originality method was begun in the summer of 2010. Contemporaneous with this study, attempts were made to fine-tune the algorithm to correct for two not necessarily common but plausible problems that could inadvertently inflate a student’s originality score.

First, within an individual writing sample, a student could repeatedly use a word that is not only a synset match, but a match that yields a particularly high $\alpha$ value (see Equation 4). Therefore, an unreasonably high originality might be result for that writing sample, when really the student had only reiterated a single word. Since students would not ordinarily be apprised of the relevant query terms for any given assignment or set of assignments, such a scenario could arise purely by chance. To offset this possibility, a “decay factor” was developed to
incrementally decrease the weight of the $\alpha$ value for any particular synset match given how many times the match has appeared before within the sample. The decay factor is set such that mentions up until a certain threshold receive the maximum value, with every subsequent mention receiving a gradually lesser value.

Second, where the evaluation of “originality” depends upon multiple query terms within the same writing sample for the set $Q$ (see Equation 6), then the distance between any two matches within a given writing sample may also prove significant. For example, in a query for the compound term “color blindness,” the occurrence of a synset match for the word “color” in the first paragraph of a writing sample may be otherwise unrelated to a synset match for “blindness” four paragraphs later. To mitigate this possibility, a “distance factor” was developed, allowing an instructor to specify a maximum distance in sentences between any two synset matches in order for their $\alpha$ value to be included in the final originality calculations for a given writing sample.

Both the decay factor and distance factor were incorporated into the Point of Originality tool as optional adjustments that could be toggled at will. In the results discussed in Section VII, the results were obtained both without any factors whatsoever and using a decay factor set to a threshold of three and a distance factor set to a maximum distance of five sentences. For the numbers recorded in the ensuing case study in Section VIII, the results were obtained only using this same set of factors.

VII. PRIOR FINDINGS

As detailed more extensively in earlier work [48], the Point of Originality tool has demonstrated statistically significant correlations between the originality values of a students’ co-blogging work and eventual paper grades assigned by the instructor. Put differently, for a set of query terms or course topics, as students’ blog post originality scores increased, students wrote better papers on those same topics.

There was likewise a marked difference between what can be defined as the “originality variance” – the difference between how the originality of a student’s blogging activity compared to that of their final papers. Students who produced more original material during the period of iterative evaluation in fact wrote nominally less original – but nevertheless better graded – papers. Yet this is, in part, accounted for by the fact that the most original students were at the height of their understanding well prior to final evaluation. These students had mastered the materials in such a way that they had an easier time writing their papers, whereas the least original students on average were only first beginning to wrestle with this content after the papers were assigned.

This lag in the originality variance demonstrates both the value of iterative exercises more generally, while underscoring the time-sensitive nature of providing feedback. Students who performed best on the essay assignment were those students with the highest originality values during what we refer to as the “lead-in period” – the period of time when students had been exposed to a set of concepts during their coursework, but had no way of knowing that they would ultimately be evaluated on those specific concepts. These students essentially had practice in the concepts at hand. If students can get “into the game” earlier in the semester, they have greater opportunities to participate in discussions, refine their understanding and “lock it down deep” so that they leave the course with a higher degree of mastery.

This observation is just as true, however, for instructors. In a large reading- and writing-intensive course, where a bulk of the work towards mastery might take place in machine-readable form, it goes without saying that it would be advantageous for the instructor to be able to use technology to monitor each student's progress. Specifically in larger gateway courses, where the odds are already stacked against student achievement and the need for interventions is more difficult to spot, students who fail to integrate completely with the class community – either because their experience comes from another discipline, or because they simply aren't accustomed to the specific class environment – are likely to suffer poor performance. Having the ability to assess students' mastery of the material, however, would enable the instructor to identify those students who are perhaps struggling or only falling behind, and to intervene to correct the students' performance.

The case study discussed in the previous sections made use of the original point of originality algorithm given in Equation 6 in order to demonstrate the broader accuracy and efficacy of the method. Although the results obtained thus far are evidence of the method’s ability to predict likely success or failure, the modifications discussed in Section VI, however, have an opportunity to further increase the tool’s predictive potential even further.

With the decay and distance factors in place, there was a sweeping, statistically significant correlation between a student’s originality during the lead-in period and his or her final paper grade. This was true for a student’s total originality during the lead-in period, and even truer of a student’s average originality during the same period. Those students, in short, who were more original during the lead-in period would eventually write better papers, period. In other words, with the decay and distance factors in place, it is possible to identify which students are most likely to perform exceptionally based either on individual instances of original expression or on a more frequent engagement, on average, with the same material.

This distinction presents an important consideration for practical application of the Point of Originality tool. If students are asked to engage in a freeform iterative activity like co-blogging, an instructor will need to be alerted to potentially struggling students based on a variety of patterns of original expression. Since students are (or here, were) free to blog on any topic of their choice, they couldn’t in fact know in advance which topics would be the subject of their later summative essay assignment. For any set of possible query terms then, simple chance might demand that some students would produce consistently original posts, while others would produce highly original individual instances of originality. The findings developed here, however, demonstrate that either type of expression is likely to result in later success. The students least likely to succeed, and thus those most requiring
pedagogical intervention, would be those whose exercise of recast terminology is most stagnant.

The following section seeks to seize on these observations by modeling a use case scenario for how the Point of Originality tool could be deployed concurrent with students’ iterative writing activities. Since students’ originality on a series of topics is predictive of their final graded evaluation on those same topics, the Point of Originality tool might be used to identify which students are likely to struggle with a particular assignment well in advance. In these instances, an instructor might thus be able to conduct any of a number of pedagogical adjustments to reinforce the relevant material, pushing students in the right direction and—hopefully—ensuring more promising outcomes.

VIII. USE CASE SCENARIO

The statistical findings noted above in Section VII were obtained from a live sample of iterative writing assignments gathered from a course on “Internet & Society” taught in the Department of Computer Science at Brandeis University in the Fall of 2008. The course was an introductory course, focused on exposing students to topics such as the social life of information, virtual communities, online privacy, intellectual property, and peer-to-peer computing. During the semester, students were responsible for producing at least two blog posts per week (of one or two paragraphs in length) on any of the topics that the course readings or lectures might have covered; students were additionally encouraged to comment on conversations initiated by their peers.

Although neither of the authors of the present study were the instructor of the Internet & Society course, the data collected and observed over its duration provides a possible use case for just how the Point of Originality might be used to conduct targeted interventions or other pedagogical adjustments. In a course like Internet & Society, where the students were engaged in a regular iterative activity in preparation for final summative evaluations, there is a protracted time period during which an instructor would benefit from the ability to isolate which students would be most likely to struggle and which would be most likely to succeed. The proven efficacy of the Point of Originality tool provides just that possibility.

All of the methodology detailed below followed more or less the same procedure adopted by the researchers when gathering their original findings in [48]; however, the ensuing discussion is aimed primarily at highlighting how an instructor might have used the Point of Originality tool for these actual students—in this actual course—had the technology already been available.

After nine weeks in the Internet & Society course (and roughly seven weeks of the co-blogging activity), students were asked to prepare a summative essay assignment on one of the books that the course had covered. The essay prompt asked students to specifically explain the concept of the “innovate commons,” and to relate this concept to other notions like “layers, resources, and control.” Each of these quoted concepts were topics that the course had touched upon over the nine-week period. Although several students had voluntarily opted to blog on some of these topics, none, at the time, could have been aware that they would ultimately be assessed on these topics in particular. Thus the nine-week interval constitutes what had earlier been referred to as the “lead-in period” for this particular set of course material.

The specific topics demanded by the essay prompt (“innovate commons, layers, resources, control”), moreover, would thus constitute optimal query terms for the Point of Originality tool. As in most summative assignments, the prompt is an attempt to assess a student’s proficiency in a fixed number of key concepts. During the co-blogging period, however, students had already had an opportunity to demonstrate their iterative understanding of those same concepts in a number of different contexts. By understanding in his or her own turn just how well or how deeply students had demonstrated their proficiency in those same concepts, an instructor would have the opportunity to anticipate which students might have particular difficulty with the assignment.

In Figure 3, we see one such case in point. This student, who will be called “Carisa,” produced thirteen posts between the beginning of her blog and the actual finalization of her essay assignment. Each of the sequential hashes from left to right at Inset 1 in Figure 3 represents one such blog post, arranged in chronological order; the circle above the hash is the visual indication of that student’s point of originality for all of the input query terms (“innovate common,” “layer,” etc.) for

![Figure 3. Carisa’s Point of Originality for Summative Assignment Query Terms](image-url)
that specific post. The larger circle, at Inset 2, represents the
student’s actual essay text, which was uploaded into the co-
blogging environment as a distinct “post” in its own right. For
our purposes, however, we are primarily concerned with the
period represented by Inset 1. This interval is what we refer to
as the “lead-in period,” the time during which all students in
the course were exposed to the material on which they would
eventually be tested without actually knowing, however, which
material was most important. Not only, however, does the lead-
in period represent the interval during which the students’ ideas
were in gestation. These earliest activities further correspond to
the information that an instructor would have access to if he or
she was to use the Point of Originality tool while the semester
was actually in progress. The values generated during the lead-
in period are, in effect, the values that represent the student’s
engagement prior to the beginning of summative evaluation. Outside of the lead-in period, the student has already performed
their summative evaluation; the course has moved on to new
topics; it is now too late to conduct the sort of intervention that
might provide alternative outcomes. Concept mastery
demonstrated during the lead-in period thus marks the first,
best possible window into a student’s iterative understanding,
and the last, best chance to actually do something about it.

For Carisa, demonstrations of this understanding were only
spotty at best. Although the student did produce one post on
IRC chats and peer-to-peer file sharing (the circle at Inset 3)
that did seem to almost perfectly align with the query terms in
question, the student’s actual expression within this post was
relatively static; the same terms (“community” as a synonym of
“commons,” for instance) were repeated a number of times.
This repetition is incidentally the type of usage that the decay
factor was developed to constrain. In the rest of the student’s
activity during this period, however, the dearth of query term
matches is arresting. Often there are no matches whatsoever;
where there are matches (as in the third through sixth posts),
we see only isolated mentions of one or two words. Carisa did,
in fact, perform the assignment as required, but although Carisa
was apparently engaged with certain of the course material
(writing, for instance, about the difference between Mac and
PC users at length), this was not necessarily the material that
best reflected what the students would later be expected to have
learned. No matter how frequently the lectures returned to this
material, or no matter how pivotal that material would be to the
course more generally, Carisa’s attentions were apparently
elsewhere.

By contrast, Figure 4 shows the co-blogging activity of a
different student, “Clair,” as reflected by the Point of
Originality tool. Here again Inset 1 represents the lead-in
period for the query terms in question. Inset 2 marks Clair’s
summative essay assignment. What is most immediately
notable about Clair’s iterative activity as given by the Point of
Originality tool is the extent to which her investment in the

FIGURE 4. CLAIR’S POINT OF ORIGINALITY FOR SUMMATIVE ASSIGNMENT QUERY TERMS
query term concepts during the co-blogging assignment frequently matches (and at one point even exceeds) her expression of those same terms in her essay, when she was explicitly asked to address those topics. The final numeric score for the “originality” of Clair’s essay assignment (after accounting for the decay factor) was 36.37. During the lead-in period, however, Clair’s earlier blog posts had recorded scores of 39.70, 34.91, 30.94, and 30.79.

What was it in Clair’s writing that brought out this particular understanding of the “innovate commons,” of “layers, resources, and control?” The fifth blog post, which received the originality score of 34.92 (represented by Inset 3 in Figure 4, and given in part in the text box at the bottom part of the image), is explicitly about none of these topics in particular. Clair’s post is on public licensing of programming code, with specific reference to the GPL or “GNU Public License.” Like Carisa, Clair does deploy some terms, like “community,” that are near synonyms for one of the query terms. Carisa, however, does not use these terms entirely in isolation. Rather, each synonymous usage is accompanied by a host of additional vocabulary that explores the same concept. For the query term “commons,” for instance, Clair produces the following sentence (with our own emphasis added):

“[The Mozilla Firefox End User License Agreement] allows someone to take code that a group of people have worked on and relicense it completely contrary to the community values”

Each of the italicized terms – “group, people, community” – is a query term match for “commons.” For the purposes of the Point of Originality tool, each of these individual terms counts towards Clair’s demonstration of mastery in the concept of “commons.” An instructor reading over this sentence would come to much the same judgment: the purpose of open licensing is indeed to stress the communal nature of the endeavor. Although the term “commons” itself appears nowhere within Clair’s post, her detailed discussion of the consequences of Mozilla’s EULA make it evident that she understands the stakes involved.

A similar pattern appears throughout Clair’s lead-in period work. While the query term concepts laid out by the essay prompt, beginning with the “innovate commons,” were specifically drawn from Lawrence Lessig’s book The Future of Ideas, some of Clair’s highest originality values on the query terms at hand come in discussion of other texts entirely. During the lead-in period, Clair’s mastery of the concepts that she will finally be tested on is not limited to a mere recitation of how those concepts fit into one particular reading. Rather, she demonstrates a consistent ability to apply those concepts in a number of different contexts. When it comes time for Clair to write her essay assignment, that essay isn’t even the place where she has explored those concepts most extensively.

It should come as no surprise that whereas Clair was one of the highest performing students on the summative essay assignment, Carisa was one of the lowest. So pronounced are the peaks and valleys between Clair and Carisa’s relative lead-in periods (Figure 3, Inset 1 and Figure 4, Inset 1, respectively) that this outcome might have been detected well in advance. Students in Internet & Society were exposed to the concept of “control” during the first week of lectures; they were exposed to the concept of the “innovate commons” just a week later. And yet during that entire period, Carisa demonstrated very little engagement with any of the concepts at hand. This is not to say that Carisa is somehow fundamentally incapable; on the contrary, Carisa’s graded score on this particular assignment was significantly lower than her performance on every other graded component of the course. This itself, however, suggests that with enough advance notice, an instructor might have spotted Carisa’s lagging performance and been able, at the very least, to make it a particular point to monitor her progress in the future. Each empty hash mark at Figure 3 Inset 1 represents something of an opportunity missed. At any of the points within the lead-in period, Carisa’s poor performance might have been prevented.

What would this sort of intervention look like? Possibly the instructor could meet with the student to discuss his or her specific interest in the course material. Possibly the instructor could simply make it a point, in his or her own teaching, to emphasize these concepts more frequently or more forcefully. Whatever the intervention, one of the benefits of the Point of Originality system is that it allows for iterative tracking in its own right. After one intervention, the instructor has the ability to see if the student’s performance does ultimately approve, and, if it doesn’t, has the opportunity to try something else. Which intervention strategies ultimately prove most successful is a pending question of live testing in future work.

Yet Clair’s performance suggests a no less pressing implication for the Point of Originality and course pedagogy. Clair, we noted earlier, actually recorded originality values commensurate with her summative essay assignment early on in the co-blogging period. Yet whereas the essay prompt was specifically directed at Lawrence Lessig’s The Future of Ideas, students did not, in fact, begin reading Lessig’s book until the sixth week of classes. Clair’s post on the user license agreements, however, and one of her highest originality scores for the query terms in question, however, was recorded in her fourth post – in the fourth week of classes. In this case, Clair demonstrated a comprehensive mastery of the ideas behind the “innovate commons” well before that material was ever explored in earnest. It would be bizarre to suggest that this is not, in fact, a positive development. But if the Point of Originality tool’s utility lies in its potential to predict student outcomes, the early extent to which success might have been predicted for Clair suggests another means by which the tool might be used.

Clair’s achievement and Carisa’s struggles came in relation to a specific subset of query terms. It is not inconceivable, however, that an instructor might encounter a class made up entirely of Clairs, or entirely of Carisas. In a course where a large number of students suggest the same lack of full mastery demonstrated by Carisa, depending on the relevance of the material, an instructor might make more even drastic pedagogical adjustments than those already suggested, perhaps rearranging the syllabus to devote more time to those particular concepts, or perhaps bringing the discrepancy directly to the class’s collective attention. Alternatively, in a course where a wide swath of students, like Clair, demonstrate sufficient mastery of a concept well in advance of that material being
covered in class, an instructor might preemptively adjust the syllabus to explore new, fresher material entirely.

All of these pedagogical adjustments are strategies that an instructor might ordinarily undertake over the course of a semester-long study. Yet in many cases, the observations of individual student behavior required – reading through each writing sample, noting a student’s iterative advancement of one particular concept, comparing it to the week prior, and so on – would take a disproportionately long period of time to fully develop. What distinguishes the Point of Originality tool’s potential is its ability to perform a number of these evaluations in concert, to generate diagnostics on-demand. “Taking the temperature” of a course becomes as easy as culling query terms from one’s own syllabus. With the time thereby saved in monitoring and self-reflection, an instructor can then turn to the arguably most important task – using those insights to make his or her students better.

IX. CONCLUSIONS AND FUTURE WORK

The technique outlined here constitutes one possible method for using the Point of Originality tool to detect trends in student expression of core course concepts in iterative writing exercises. Where student use of these concepts as identified by the tool is most fleeting is where students are most likely to encounter difficulties in later summative assignments. Detecting these instances in advance provides one opportunity for instructors to monitor the efficacy of their own teaching, to detect broad patterns in student behavior, and to make adjustments to pedagogical practice accordingly.

Future work in this project aims to pursue longitudinal testing of the tool within a series of actual class environments, not only to determine the practical efficacy of the tool, but to moreover isolate optimal strategies for pedagogical intervention. Although the predictive potential of the Point of Originality can determine, with statistically significant accuracy, which students are least likely to succeed in a particular assignment, the hope of the researchers would be that it might also be used to track those students’ progress once adjustments have been made.

A second benefit of the tool, and another possible avenue for future work, lies in its implications for syllabus creation and maintenance. While course syllabi are normally created at the beginning of a semester and adhered to from week to week with only minor adjustments, the ability of the Point of Originality to determine how all members of a class are approaching the material might permit an instructor to adopt a more fluid course structure. At a minimum, with the additional time freed up by use of the Point of Originality, it would be our hope that more instructors would have a yet greater opportunity to refine their teaching method.

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