Categorization, Intersectionality, and Learning Analytics

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ABSTRACT: Learning analytics often relies on data produced by education systems which include traditional categorical descriptors of identity. Uncritical use of these reductive categories obscures the complexity of identity and masks the unique experience of each student. If learning analytics is to accomplish its goal of understanding and improving teaching and learning for all students, it must examine the methods it uses to account for social identity more closely. In this work, we describe how feminist studies of intersectionality have informed our own analysis of how social identity might influence student performance in an array of large introductory courses.

Keywords: Social Identity; Categorization; Intersectionality; Personalization

1 INTRODUCTION

Data sets used in learning analytics regularly record categorical descriptors of each individual's identity: gender, underrepresented and first generation status, residency, race. Analyses based on these descriptors often proceed along individual dimensions; comparing male and female, first and non-first-gen, or racial and ethnic categories. Such analyses elide over the lived experience of identity, which is neither simply categorical nor unidimensional. This reality, long recognized by those who study social identity, is often described as intersectionality (Davis, 1981; Crenshaw, 1989). This use of reductive categorization to describe complex individuals is a persistent problem in the world of big data. Cheney-Lippold (2017) refers to these categories as "measureable types", distinguishing (for example) between gender as a lived experience and 'gender' as a label within a data set. In this work, we will adopt his convention, denoting the simple, transcoded measurable types which stand in for complex social identities by enclosing them in single quotes.

If we are to fully realize the ambition of learning analytics, "to understand and optimize learning and the environments in which it occurs" (Siemans & Long, 2011), we must move beyond the information loss associated with the use of measureable types and strive to characterize the individuals we study in a holistic, multidimensional way. In this brief research abstract, we describe essential elements of our efforts to move beyond the reductive characterization of our learners. We begin with an overview of methodological approaches to dealing with intersectionality. This is followed by a concrete example, based on efforts to understand gendered performance differences in large introductory science courses. We conclude with some lessons learned and a vision for using analytics for deeper personalization at scale.

2 METHODOLOGIES FOR ADDRESSING INTERSECTIONALITY

There are many approaches to confronting intersectionality when attempting to understand the relation between social identity and subject formations. McCall (2005) provides a useful framework for considering the range of possibilities, though we recognize the irony of discretely classifying methods for addressing intersectionality.

Anticategorical Complexity asserts that social life are irreducibly complex, and that categories imposed on them usually exist to produce and enforce inequalities. Nonreductive, this approach is best able to capture the full complexity of each individual's social identity. It is, in a sense, a demand for absolute personalization: for seeing each individual only as an individual, not a member of any collective category. *Intracategorical Complexity* aims to explore the deeper, often hidden diversity which exists within a cell (or cells) of traditionally constructed categories. It focuses on deconstructing the apparent homogeneity of a data category, critiquing the uncritical use of measureable types so common in data science. Finally, *Intercategorical Complexity* takes traditional categories as provisional, and uses them to frame analyses aimed at documenting existing "relationships of inequality" among these groups.

3 INTERSECTIONAL EXPLORATIONS OF ACADEMIC PERFORMANCE

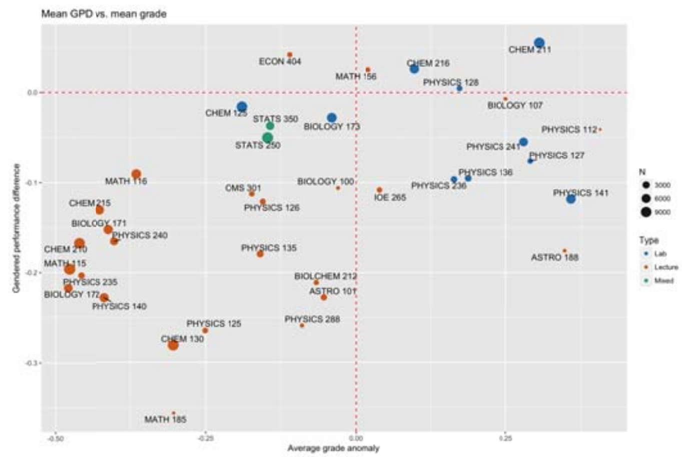
To illustrate the importance of an intersectional approach in learning analytics, we provide a concrete example – studies of gendered performance difference in large introductory science courses. In this work, we compare the performance of each student to a simple expectation – their performance in all other courses completed at the same institution. We call this difference between GPA in all other classes and course grade a student's 'grade anomaly'; a course-and-student-specific measure of better or worse-than-expected performance. Courses which award comparatively low grades have average grade anomalies (AGAs) which are negative; those which award comparatively high grades have AGAs which are positive. In this approach, the performance of two groups of students may be compared by examining the difference in AGA for the two groups.

Our studies began as an effort to explore gendered performance differences (GPD = AGA_{female}-AGA_{male}) in individual courses. They have since expanded to examine overall AGA and GPD across a wide range of large introductory courses. Figure 1 plots GPD vs. AGA for an array of 37 large introductory courses in science, engineering, and economics. This figure shows that while lecture courses exhibit large gendered performance differences, lab courses typically do not. These GPDs are persistent over many years and independent of instructor identity. They cannot be explained by reference to any other prior information available in our student record system (Blinded internal study, 2016).

We interpret these unexplained GPDs as signs of structural inequity in these courses and are currently exploring several approaches to eliminating them. Since the courses are unusual in their reliance on high stakes, timed examinations for determining grades, we suspect that stereotype threat associated with social identity may play a role in the creation of these inequities. This possibility makes our understanding of social identity especially important in this context, and has driven us to investigate our use of traditionally constructed categories in characterizing students.

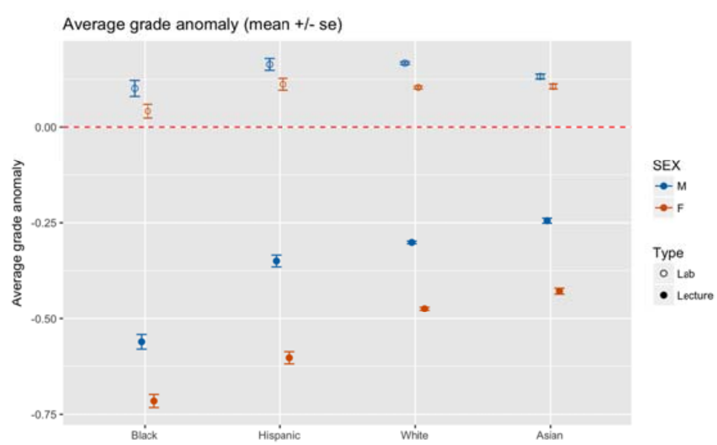
Our original analysis relies on a classic binary characterization of student identity through a single measureable type – ‘male’ or ‘female’ – contained within our student record system. The widespread and persistent appearance of GPDs demonstrates that the label ‘female’ is correlated with underperformance in these courses, but it does little to reveal what about students actually *causes* underperformance.

Figure 1: Gendered Performance Diff. is plotted vs. Average Grade Anomaly for a series of 37 lecture, lab, and mixed format courses across a range disciplines. While lecture courses show substantial GPDs, lab courses do not.



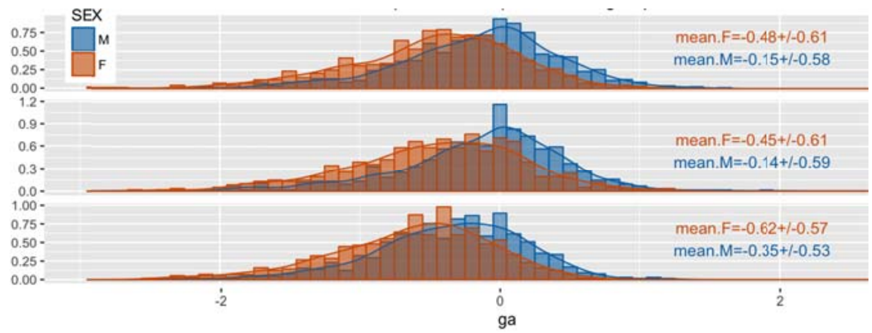
An application of the *Intercategorical Complexity* approach to better and worse-than-expected performance might begin (for example) by examining the intersection of ‘gender’ and ‘ethnicity’. Figure 2 shows the results of such an examination, comparing AGA in an array of biology, chemistry, physics, and economics courses for male and female students in four ‘ethnicity’ groups. Clearly ‘gender’ is not the only factor significally affecting AGAs. Indeed ‘Black male’ students underperform relative to ‘White female’ and ‘Asian female’ students. In many analyses, these potentially intersecting identities are treated as independent. In fact they may interact, creating non-linear effects. If we pursue solutions to student performance gaps with *only* the lens of ‘gender’, we would miss essential elements of the student experience.

Figure 2: Average grade anomalies are shown for both ‘male’ and ‘female’ students in four ‘ethnicity’ groups in six years of data drawn from a series of biology, chemistry, physics and economics lecture and lab courses.



To apply the *Intracategorical Complexity* approach to this analysis, we take one category of students – ‘male’ or ‘female’ for example – and use additional information to probe the correlates of underperformance within it more deeply. To illuminate this possibility, Figure 3 shows the distribution of grade anomalies for individual ‘male’ and ‘female’ students in one of these courses over three successive fall terms. While a statistically and materially significant difference in average grade anomaly clearly exists, there is enormous overlap among the outcomes of individuals, with many ‘male’ students performing worse-than-expected and many ‘female’ students performing better-than-expected. This substantial variation within measureable types drives us to consider more closely what other, perhaps unmeasured factors might be responsible for underperformance. Are there some ‘female’ students immune from social identity threat; some ‘male’ students subject to it?

Figure 3: Shows grade anomaly distributions for all ‘male’ and ‘female’ students in 3 years of data from a large lecture course.



The ultimate goal might be to approach the data with the lens of *Anticategorical Complexity*, resisting the temptation to reduce the unique social identities of students to traditional categories of measureable types entirely. When we speak of true personalization at scale, this, we believe, should be the goal: to spend most analytic effort understanding and improving the experience of individuals, rather than ending our analysis with an array of traditionally constructed measureable types.

4 IMPLICATIONS

It is common to characterize students using only the traditionally constructed measureable types: researchers are inclined to use the data they have. If the learning analytics community is going to achieve its goals, it will have to maintain a rigorously critical stance toward traditional measureable types. The feminist literature of intersectionality provides important insight into how this work might proceed, and those using data to understand and improve teaching and learning have much to learn from it.

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