Taxonomizing Features and Methods for Identifying At-Risk Students in Computing Courses

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ABSTRACT

Since computing education began, we have sought to learn why students struggle in computer science and how to identify these at-risk students as early as possible. Due to the increasing availability of instrumented coding tools in introductory CS courses, the amount of direct observational data of student working patterns has increased significantly in the past decade, leading to a flurry of attempts to identify at-risk students using data mining techniques on code artifacts. The goal of this work is to produce a systematic literature review to describe the breadth of work being done on the identification of at-risk students in computing courses. In addition to the review itself, which will summarize key areas of work being completed in the field, we will present a taxonomy (based on data sources, methods, and contexts) to classify work in the area.

CCS CONCEPTS

• Social and professional topics → Computer science education;

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KEYWORDS

educational data mining, analytics

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1 INTRODUCTION

The adoption of instrumented coding tools in introductory CS courses has created an opportunity to directly observe and react to student data. This has lead to increased interest in models that can be used to identify at-risk students in computing courses [3, 4].

This burst of work has lead to a split in the community. Earlier work often relied on the use of student preferences or demographic factors that could be gathered as or before a course began [5]. However, more recent attempts frequently eschew these features, focusing instead on data generated in the course [1, 2]. This working group seeks to connect the various communities – including those outside of computing education – that are supporting the work of identifying at-risk students in computing courses.

The goal of this work is to produce a systematic literature review to describe the breadth of work being done on the identification of at-risk students in computing courses. In addition to the review itself, which will summarize key areas of work being completed in the field, we will present a taxonomy (based on data sources, methods, and contexts) to classify work in the area. We hope the review and accompanying taxonomy will help to connect researchers in

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this area by identifying clusters of related work being published in different venues and highlighting opportunities for collaboration, integration, and broader dissemination.

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