
Half Title Page

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To my wife Ana and my son Cristóbal

Cristóbal Romero

To my wife Inma and my daughter Marta

Sebastián Ventura

To my wife Ekaterina and my daughter Aleksandra

Mykola Pechenizkiy

To my wife Adriana and my daughter Maria

Ryan S. J. d. Baker



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Preface

The Purpose of This Book

The goal of this book is to provide an overview of the current state of knowledge of educational data mining (EDM). The primary goal of EDM is to use large-scale educational data sets to better understand learning and to inform the learning process. Although researchers have been studying human learning for over a century, what is different about EDM is that it makes use not of experimental subjects learning a contrived task for 20 min in a lab setting; rather, it typically uses data from students learning school subjects, often over the course of an entire school year. For example, it is possible to observe students learning a skill over an eight-month interval and make discoveries about what types of activities result in better long-term learning, to learn about the impact of what time students start their homework has on classroom performance, or to understand how the length of time students spend reading feedback on their work impacts the quality of their later efforts.

In order to conduct EDM, researchers use a variety of sources of data such as intelligent computer tutors, classic computer-based educational systems, online class discussion forums, electronic teacher gradebooks, school-level data on student enrolment, and standardized tests. Many of these sources have existed for decades or, in the case of standardized testing, about 2000 years. What has recently changed is the rapid improvement in storage and communication provided by computers, which greatly simplifies the task of collecting and collating large data sets. This explosion of data has revolutionized the way we study the learning process.

In many ways, this change parallels that of bioinformatics 20 years earlier: an explosion of available data revolutionized how much research in biology was conducted. However, the larger number of data was only part of the story. It was also necessary to discover, adapt, or invent computational techniques for analyzing and understanding this new, vast quantity of data. Bioinformatics did this by applying computer science techniques such as data mining and pattern recognition to the data, and the result has revolutionized research in biology. Similarly, EDM has the necessary sources of data. More and more schools are using educational software that is capable of recording for later analysis every action by the student and the computer. Within the United States, an emphasis on educational accountability and high stakes standardized tests has resulted in large electronic databases of student performance. In addition to these data, what we need are the appropriate computational and statistical frameworks, techniques to make sense of the data, as well as researchers to ask the right questions of the data.

No one discipline has the necessary expertise to conduct EDM research. Thus, the community, as can be seen by the chapter authors of this book, is composed of people from multiple disciplines. Computer science provides expertise in working with large quantities of data, both in terms of machine learning and data-mining techniques that scale gracefully to data sets with millions of records, as well as address real-world concerns such as “scrubbing” data to ensure systematic errors in the source data do not lead to erroneous results. Statisticians and psychometricians provide expertise in understanding how to properly analyze complex study designs, and properly adjust for the fact that most educational data are not from a classic randomized controlled study. These two communities

are strong in statistical and computational techniques, but techniques and data are not sufficient to advance a scientific domain; researchers with basic understanding of the teaching and learning process are also required. Thus, education researchers and psychologists are key participants in the EDM community.

Main Avenues of Research in Educational Data Mining

There are three major avenues of research in EDM. They nicely align with the classic who–what–where–when interrogatives.

The first avenue is work on developing computational tools and techniques, determining which ones are best suited to working with large educational data sets, and finding best practices for evaluation metrics and model fitting. Examples of such efforts include experimenting with different visualization techniques for how to look at and make sense of the data. Since educational data sets are often longitudinal, encompassing months and sometimes years, and rich interactions with the student can occur during that time, some means of making sense of the data is needed. Another common approach in EDM is using variants of learning curves to track changes in student knowledge. Learning curves are some of the oldest techniques in cognitive psychology, so EDM efforts focus on examining more flexible functional forms, and discovering what other factors, such as student engagement with the learning process, are important to include. One difficulty with complex modeling in EDM is there is often no way of determining the best parameters for a particular model. Well-known techniques such as hill climbing can become trapped in local maxima. Thus, empirical work about which model-fitting techniques perform well for EDM tasks is necessary.

This work on extending and better understanding our computational toolkit is a necessary foundation to EDM. Work in this area focuses on how we can extract information from data. At present, although a majority of EDM research is in this avenue, the other two are not less important—just less explored.

The second avenue is determining what questions we should ask the data. There are several obvious candidates: Does the class understand the material well enough to go on? Do any students require remedial instruction? Which students are likely to need academic counseling to complete school successfully? These are questions that have been asked and answered by teachers for millennia. EDM certainly enables us to be data driven and to answer such questions more accurately; however, EDM's potential is much greater. The enormous data and computational resources are a tremendous opportunity, and one of the hardest tasks is capitalizing on it: what are new and interesting questions we can answer by using EDM? For example, in educational settings there are many advantages of group projects. Drawbacks are that it can be hard to attribute credit and, perhaps more importantly, to determine which groups are having difficulties—perhaps even before the group itself realizes. A tool that is able to analyze student conversations and activity, and automatically highlight potential problems for the instructor would be powerful, and has no good analog in the days before computers and records of past student collaborations were easily available. Looking into the future, it would be useful if we could determine if a particular student would be better served by having a different classroom teacher, not because one teacher is overall a better choice, but because for this type of student the

teacher is a better choice. The first example is at the edge of what EDM is capable; the second is, for now, beyond our capabilities.

This job of stretching our horizons and determining what are new, exciting questions to ask the data is necessary for EDM to grow.

The third avenue of EDM is finding who are educational stakeholders who could benefit from the richer reporting made possible with EDM. Obvious interested parties are students and teachers. However, what of the student's parents? Would it make sense for them to receive reports? Aside from report cards and parent-teacher conferences, there is little communication to parents about their child's performance. Most parents are too busy for a detailed report of their child's school day, but what of some distilled information? A system that informed parents if their child did not complete the homework that was due that day could be beneficial. Similarly, if a student's performance noticeably declines, such a change would be detectable using EDM and the parents could be informed. Other stakeholders include school principals, who could be informed of teachers who were struggling relative to peers, and areas in which the school was performing poorly. Finally, there are the students themselves. Although students currently receive an array of grades on homeworks, quizzes, and exams, they receive much less larger-grain information, such as using the student's past performance to suggest classes to take, or that the student's homework scores are lower than expected based on exam performance. Note that such features also change the context of educational data as something that is used in the classroom, to something that is potentially used in a completely different place.

Research in this area focuses on expanding the list of stakeholders for whom we can provide information, and where this information is received. Although there is much potential work in this area that is not technically demanding, notifying parents of missed homework assignments is simple enough, such work has to integrate with a school's IT infrastructure, and changes the ground rules. Previously teachers and students controlled information flow with parents, now parents are getting information directly. Overcoming such issues is challenging. Therefore, this area has seen some attention, but is relatively unexplored by EDM researchers.

The field of EDM has grown substantially in the past five years, with the first workshop referred to as "Educational data mining" occurring in 2005. Since then, it has held its third international conference in 2010, had one book published, has its own online journal, and is now having this book published. This growth is exciting for multiple reasons. First, education is a fundamentally important topic, rivaled only by medicine and health, which cuts across countries and cultures. Being able to better answer age-old questions in education, as well as find ways to answer questions that have not yet been asked, is an activity that will have broad impact on humanity. Second, doing effective educational research is no longer about having a large team of graduate assistants to score and code data, and having sufficient offices with filing cabinets to store the results. There are public repositories of educational data sets for others to try their hand at EDM, and anyone with a computer and Internet connection can join the community. Thus, a much larger and broader population can participate in helping improve the state of education.

This book is a good first step for anyone wishing to join the EDM community, or for active researchers wishing to keep abreast of the field. The chapters are written by key EDM researchers, and cover many of the field's essential topics. Thus, the reader gets a broad treatment of the field by those on the front lines.

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