PREDICTIVE MODELING OF K-12 ACADEMIC OUTCOMES

A Primer for Researchers Working with Education Data

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What Is Predictive Modeling?

Predictive modeling estimates individuals' future outcomes or their probabilities of future outcomes. It does this by building and testing a model using data on similar individuals whose outcomes are already known. Commonly used in business and marketing research, predictive modeling is gaining currency in many social policy domains as a way to identify individuals who may benefit from targeted intervention. When results are interpreted correctly, predictive modeling offers benefits to those engaged in continuous improvement efforts and those who are looking to allocate resources more efficiently.

Why Use Predictive Modeling in Education?

Schools and school districts often use early warning systems to identify students who are at risk of not meeting key academic outcomes, such as graduating on time or passing state exams.[1] Early warning systems typically use student-level data to generate a limited set of indicators to classify whether students are at risk. For example, the risk of not graduating from high school is commonly estimated by the so-called ABC indicators of attendance, behavior, and course performance.[2] An indicator-based approach typically produces a binary measure (at risk or not at risk) or a categorical measure of risk (for example, low, medium, or high) based on a snapshot of readily available measures of student behavior and performance.

Yet education systems are increasingly creating rich, longitudinal data sets with frequent, and even real-time, data updates of many student measures, including daily attendance, homework submissions, and exam scores. These data sets provide an opportunity for district

[1] For example, see Frazelle and Nagel (2015); George Washington University (2012); Stuit et al. (2016); Therriault et al. (2010); Therriault et al. (2013).

[2] Allensworth and Easton (2007); Balfanz, Herzog, and Mac Iver (2007); Balfanz, Wang, and Byrnes (2010); Celio (2009a, 2009b); Frazelle and Nagel (2015); Mac Iver (2010); Mac Iver and Mac Iver (2009); Roderick (1993); Uekawa, Merola, Fernandez, and Porowski (2010).

and school staff members to move beyond an indicators-based approach and instead employ new methods to compute more frequent, more accurate, and more nuanced predictions of student risk.

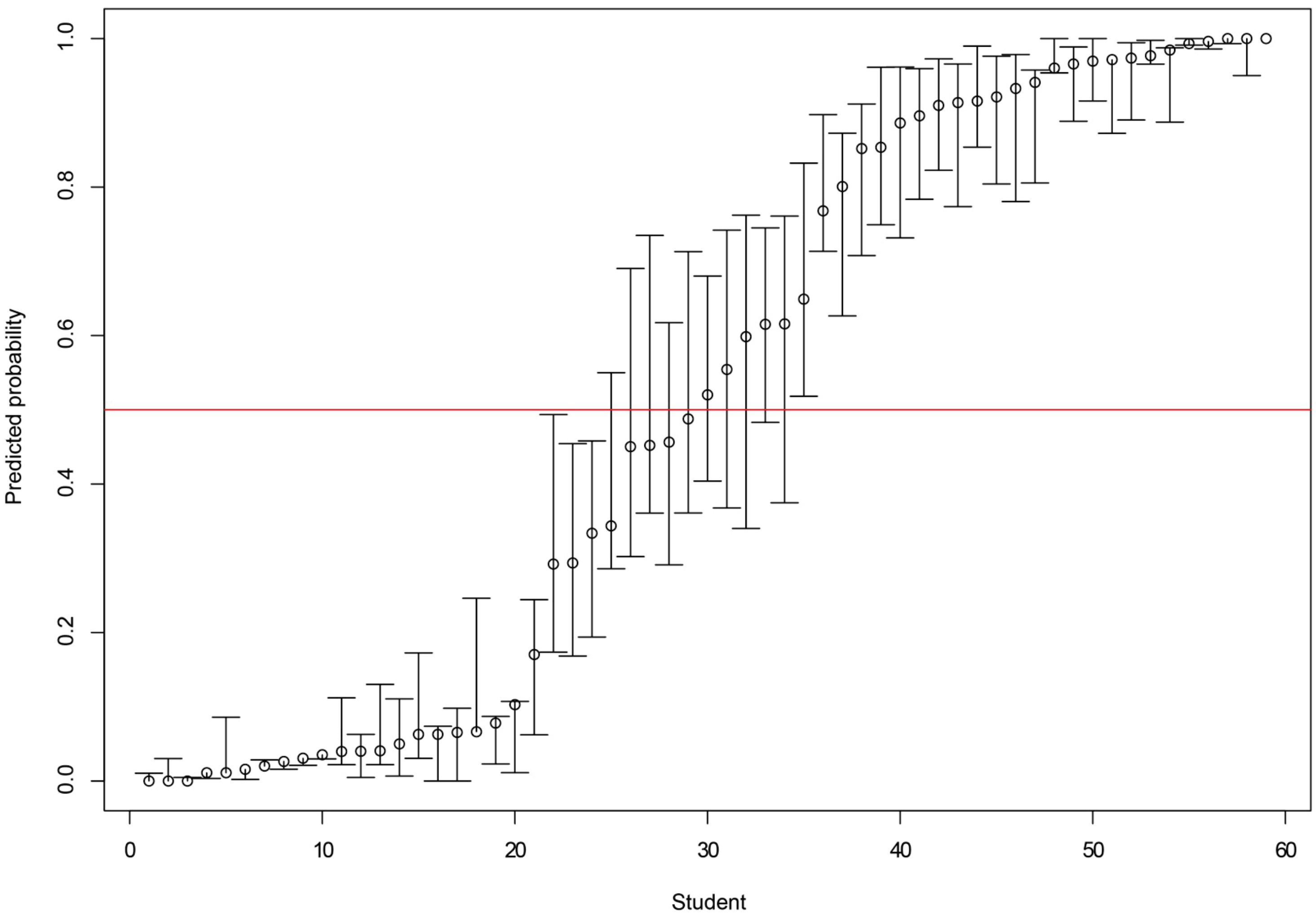
For these reasons, MDRC has been exploring the value of predictive modeling. MDRC researchers have developed and implemented a comprehensive predictive modeling framework that allows for rapid and iterative estimation of a *continuous* measure of risk (a probability between 0 and 1 of not achieving an outcome) for each student at a point in time. The framework was developed during a partnership with New Visions for Public Schools (NVPS), a nonprofit organization that works with more than 200 public schools in New York City. The framework has so far been implemented with data from its network of 70 high schools to estimate students' risk of not graduating on time and of not passing the state algebra exam required for graduation.

Consider an example in which midway through ninth grade, district administrators and educators want to know each student's risk of not graduating from high school on time. With the common ABC indicators approach, a student with a low attendance rate, behavior incidents, or course failures may be designated as having moderate or high risk of not graduating at the end of twelfth grade, depending on how the student's first-semester outcomes (and possibly eighth-grade outcomes) compare with district-specified thresholds of these ABC indicator measures.

With a predictive modeling approach, instead of a parsimonious set of summary measures (the indicators), hundreds of measures can be considered for determining students' risk. Not only students' overall first-semester attendance rates but their attendance pattern can be considered — good attendance on average could be masking a drop-off later in the semester or a large gap at some point. Nonacademic measures, such as involvement in the child welfare or justice system, if available, can also be taken into account. The information from a large number of measures can be extracted with machine learning (though sometimes a simple regression model may work just as well) and summarized in a single, continuous estimate of risk. Instead of a student being designated as at moderate or high risk, she is determined to have, for example, a 70 percent chance of not graduating on time, plus or minus 5 percentage points (with values closer to 70 percent being more likely).

Such estimates allow students to be ranked by their risk levels, and thresholds can be determined for particular interventions. Figure 1 illustrates results that could be presented for a hypothetical school. It shows each student's predicted probability (indicated by a circle) of not achieving a particular milestone, such as on-time graduation from high school. The figure also shows the estimated uncertainty interval around each prediction (the vertical line). The students have been ranked by their predicted probabilities. Such a plot reveals the variation across students in the school and the risk levels around which students may cluster.

Figure 1. Predicted Probabilities of Not Achieving a Milestone and Estimated Uncertainty Intervals, by Student at a Hypothetical School, Ranked by Probability



Looking at the distributions of risk across and within schools may provide new insights about variation in students' needs. For example, among those students classified as "high risk" by an indicators approach, the estimates from predictive modeling may reveal substantial variation in risk levels. This can be combined with descriptive analyses of students' academic progress within different ranges of risk to reveal particular factors that correlate with risk level. Finally, at the end of ninth grade, all students' risk estimates can be updated with new information — both the model and the predictions are updated. Administrators and educators can then track students' changes in risk on dashboards or other communication systems.

What Is MDRC's Approach to Predictive Modeling?

MDRC's approach to predictive modeling of student risk has the following features:

- **It relies on close partnership with practitioners.** Because policy and practice can change during and between school years, researchers need to work with practitioners to deepen their understanding of how to use and create measures from existing data sets, interpret results correctly, and maximize the usefulness of results.

- **It produces results that capture important variation between students in levels of risk and allows for students to be ranked by their risk estimates.** A predicted likelihood between 0 and 1 of not achieving an outcome provides more information about a student's risk than a category can. Also, assessing students by a continuous measure of risk better allows administrators to rank them in priority for different types of interventions.

- **It uses an analytic framework with specified decision rules and field-tested statistical code.** The framework includes analytic steps focused on (1) identifying the best samples for training the statistical model and computing predictions; (2) processing data (for example, handling missing values, creating aggregate measures that extract useful information such as changes in daily attendance, and identifying and creating measures that have the same meaning over time); (3) selecting measures to include in modeling (relying on a combination of substantive knowledge and data-adaptive algorithms); (4) identifying the best modeling methodology; (5) estimating uncertainty in predictions; and (6) summarizing and interpreting results.

- **It extracts as much information as possible from data, allowing for hundreds of measures to be considered as potential predictors in modeling.** In MDRC's framework, the modeling incorporates both standard regression-based approaches and machine learning algorithms, which can search very large numbers of measures and let the data determine what form a statistical model should take. MDRC's approach compares multiple models and selects the best one based on its predictive performance in new samples (that is, data that were not used to train the model; this helps avoid overfitting, in which the model does not adequately capture underlying relationships in the data and therefore does not generalize well to new data). These comparisons are done with cross-validation, a data resampling method that mimics repeatedly fitting a model in one sample and then evaluating it in a different sample.

When researchers consider multiple models or multiple machine learning algorithms, it is known as "ensemble learning." The way that MDRC researchers employ ensemble learning draws on both substantive expertise — through the parametric models specified by researchers based on their knowledge of which predictors matter — and the data-adaptive techniques used by machine learning algorithms. The researchers assess predictive performance in a variety of ways, emphasizing model performance measures that align with partners' priorities for how the results will be used. For example, by focusing on the metrics of sensitivity and specificity, MDRC aims to maximize identification of truly at-risk students while minimizing false alarms.

- **It allows for rapid iteration and replication.** As described above, MDRC has developed a repeatable multistep framework that allows one to update predictive models as new information becomes available and to easily replicate the process to predict additional milestones. The ability to rapidly iterate is an advantage over indicator-based systems. Districts creating such systems tend to combine indicators from published literature and descriptive analyses and use subjective decisions linked to district priorities to determine the final set of indicators. Such an approach makes updating time-consuming, especially when changing the outcome to a different milestone (for example, from failure to graduate to course failure).

- **It estimates uncertainty in prediction results.** As with any statistical procedure, the estimates of students' likelihoods of not achieving milestones have uncertainty, which is typically ignored in indicator-based approaches and even other predictive modeling frameworks. MDRC uses a nonparametric bootstrap procedure to estimate uncertainty and provide lower and upper bounds of predicted likelihoods. The nonparametric bootstrap procedure resamples data in order to mimic repeated draws from a population, and the entire analytic process can be repeated in each draw so that variation across samples can be estimated.

- **It guides practitioners in maximizing use of results.** After producing individual predictions of whether each student will fail to meet a particular milestone, and estimates of uncertainty in those predictions, MDRC works with partners to provide post-hoc analyses of predicted likelihoods that summarize variation across schools and subgroups of students. MDRC also guides practitioners in understanding the value and limitations of the predictions and in communicating results to school leaders and teachers.

What Are MDRC's Future Directions in Predictive Modeling of Academic Outcomes?

Researchers at MDRC are investigating ways to improve its predictive modeling of student risk. They are investigating whether different types of data — both from the education system and beyond — could improve the accuracy of predictions, especially predictions of long-term outcomes made early in students' careers. In particular, they are investigating whether nonacademic data, such as students' receipt of social services, or additional academic data that districts are increasingly collecting, such as homework completion and other course-level metrics, can improve predictive models for a variety of outcomes. MDRC researchers are also working to make iteration of the framework more efficient, by streamlining data processing steps and speeding up computing. In addition, MDRC is investigating methodological questions such as the extent to which and under what circumstances machine learning adds value, as well as which machine learning algorithms might be most valuable.

MDRC can support district partners in several ways: First, its researchers can help assess whether districts have the organizational capacity and the data to support predictive modeling and whether it is worthwhile for their particular needs. Where predictive modeling is suitable, MDRC researchers can help districts make the most of the results to guide decision-making. Districts interested in this approach might benefit from incorporating the results — both individual predictions and summaries across students, grades, and schools — into their dashboards and other data visualization and data sharing systems. MDRC can also provide analyses to help educators decide what to do next — how best to intervene and for whom.

Definitions of Technical Terms

Machine learning: Machine learning refers to methods that automate model building using iterative algorithms — that is, a series of steps that continuously adjust for better predictive performance — rather than relying on functional forms (specifications of the independent variables and the types of relationships between the variables and the outcome) specified by an analyst. Examples of machine learning algorithms that MDRC researchers have employed include decision trees, random forests, stepwise regression, k-nearest neighbors, support vector machines, and others.

Cross-validation: The MDRC framework uses *v*-fold cross-validation in which the data with known outcomes (for example, whether students graduated or not) are partitioned into a certain number (*v*) of subsamples (or folds). A common value for *v* is 5, but other values are used too, often driven by the sample size. A model is fit in all but one of the folds, and measures of performance are computed in the remaining, "validation" fold. The process is repeated *v* times such that each fold takes a turn as the validation fold. The averages of the performance measures are computed across all validation folds. The entire process can be repeated multiple times in order to reduce the variance of the cross-validated estimates.

Ensemble learning: Ensemble learning allows an analyst to consider multiple models or machine learning algorithms in a systematic and prespecified way so that the optimal model or algorithm, according to a performance measure of interest, is selected and used for prediction.

Sensitivity and specificity: When the outcome of interest is failing to achieve a milestone, sensitivity is the proportion of those who actually fail to achieve it who are correctly predicted as failing (based on a predetermined threshold in estimated continuous likelihood to fail). The specificity is the proportion of those who actually do achieve the milestone who are correctly predicted as doing so. The false positive rate is equal to 1 – specificity. Often it may make sense to find a model that makes the best trade-offs between sensitivity and specificity. Plotting and computing the area under receiver operating characteristic (ROC) curves is a useful way to summarize the trade-offs across all possible thresholds for designating at-risk students.

Nonparametric bootstrap: With a nonparametric bootstrap, the data are resampled with replacement (that is, observations in the first draw are eligible for selection in subsequent draws) a large number of times (say, 1,000), and analyses are repeated within each resample. The resulting set of 1,000 estimates provides an approximation of the sampling distribution of the estimators of interest. When MDRC researchers apply the nonparametric bootstrap to predictive modeling, it produces 1,000 predicted likelihoods for each student. The percentiles from 2.5 to 97.5 provide a range with a 95 percent chance of containing a student's true likelihood, with values closer to the center of the distribution being more likely.

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