Data Visualization in Public Education: Longitudinal Student-, Intervention-, School-, and District-Level Performance Modeling

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ABSTRACT

Accountability seems forever engrained into the K-12 environment, as has been the expectation of delivering quality education to school aged children and adolescents. Yet, repeated failure of this expectation has focused the public's and policy maker's attention on the limitations of major accountability systems. This paper explores applications of machine learning, predictive analytics, and data visualization to student information available to educational decision makers. In particular, we demonstrate how to use individual academic performance histories to identify "at-risk" students in real time for advising, academic coaching, and other support services and how to aggregate longitudinal data at the school or district level for system modeling, profiling, comparison, and intervention evaluation.

OBJECTIVE

This research demonstrates how predictive analytics applied to school student information system (SIS) records can be used to (1) greatly benefit student advising and activities such as academic coaching/mentoring for at-risk students, (2) assess and evaluate the impact of newly introduced educational interventions, and (3) provide tools for longitudinal assessment and evaluation of schools and/or school districts.

THEORETICAL PERSPECTIVE

Better decision making is desired at all levels of public and private education and district/school accountability and student information systems (SIS) are being developed and deployed rapidly throughout K-12 and higher education to meet this need (Salpeter, 2004; Bowers, 2017). Sometimes simple, sometimes elaborate, SIS platforms are notable in their data capture capability but often limited in their predictive analytic capability. Moreover, data from SIS records – often most easily available only for the current year - coupled with specific and local reporting needs of building administrators discourages SIS developers from providing anything more than rudimentary data analytics. This is offset by the growing number of educational predictive analytic companies and services.

Effective, informed decision making requires timely information based on data. That data must be systematically collected, organized, and reduced around a problem before it can have potential impact. Even a SIS platform that provides systematic data capture and organization is of limited utility in the absence of analytical (data reduction) systems.

Visual analytics are sought for their ability to clarify both problems and solutions. When coupled with extensive data, these tools can be very powerful mechanisms for isolating problems as well as showing solution paths. Through predictive analytics and innovative data visualization, longitudinal SIS data can be leveraged to facilitate teacher-, school-, and district-level decision-making (Van Kannel-Ray, et.al., 2008, 2009; Lacefield, et.al., 2010, 2011; Applegate, et.al., 2012).

METHODOLOGY

Participants, Data Sources, and Procedures

Our research and evaluation team at a large regional state university worked with other staff to conduct two major, 6-year overlapping, school improvement projects involving partner schools and districts in southwestern Michigan, northern Ohio, and Illinois from 2002 through 2012. Throughout this time period, we had SIS data sharing agreements, approved by the respective IRBs for annual reporting, school staff decision-making, and assistance and intervention evaluation.

SIS information was gathered at the beginning, middle, and end of each school year, including academic, attendance, behavioral, and demographic data; then collated and entered into MS Access databases eventually containing historical records for more than 26,000 students over the 10-year period, from 6th through 12th grade. The projects provided data analysis and information to collaborating school system staff as well as a variety of other student and school-level support and enhancement functions through a network of project site coordinators. Following the completion of the projects, the databases were de-identified for future research, demonstration, and dissemination purposes.

Harvested SIS data included the following constructs/variables: academic grade information (every grade datum from every teacher in every course every marking period); attendance data (summarized by marking period); behavioral data (also summarized by marking period), and student demographic data. Due to participating schools operating with substantially different policies related to behavior and attendance, we are only presenting findings related to achievement measures. Moreover, participating schools organized the school year differently, e.g., 4 or 6 marking periods, quarters, 2 or 3 semesters, etc. These patterns were frequently changed over short intervals of only two or three years.

Academic Grade Data. Our operational definition is that grades are crude evaluations of the degree to which teacher expectations are being met in typical but highly variable performance contexts. Pooled, averaged, and smoothed over time, they provide a basis by which people make decisions (parents, teachers, administrators, admissions officers, employers, etc.). Therefore, they are important within the public school system and beyond.

Course Content and Subject Area. The complete course catalogue for each participating school was simplified by aggregating courses into broad content areas for Mathematics, Science, Social Studies, and Language Arts. For example, high school mathematics classes such as Algebra I, II, Geometry, Calculus I, Business Math, etc. were classified as "Mathematics." Further aggregation levels included All-Core or Non-Core or All-Coursework. Course classification was tracked and reconsidered annually as schools added and retired courses through normal curriculum evaluation processes.

Student Performance Trajectories. Due to different schools operating under different reporting time-lines and irregularities such as repeated grades, student mobility (in- or out-bound transfers), and student attrition (drop-outs), we developed techniques to "fit" everyone and every school situation into a common historical timeline modelled on the typical grade level system. This timeline begins at 6.0, the entry point into middle school. It extends to 9.0, the entry point into high school and beyond to 13.0, the point of graduation and entry into post-secondary experiences.

DATA ANALYSIS

Data Smoothing

Grade data is extremely noisy and arrives at many different marking period points on a timeline. There are many techniques for data smoothing, one we illustrate here, e.g., Bezier curves (Bourke, 1996), as well as different statistical estimation and visualization techniques. Bezier curve trajectories stay in-between the data points in a sorted time-series. They also pass through the first and the last data point. Between the end points, the curves are continuous and can be differentiated as well as evaluated at any intermediate point. Thus, Bezier curves smooth large data point fluctuations and improve the visibility of the patterns unfolding. They also meet a key requirement which is the ability to estimate student performance in-between marking period grading points, however many there are or when they occur.

Machine Classification of Student Performance

To determine whether students were experiencing academic difficulty, we needed techniques to identify at-risk students. Typically, this is accomplished by word-of-mouth and staff recommendations. Prior research, however, suggests these communications show weak linkages to empirical measures (Lacefield, et.al., 2012). We trained and evaluated several machine learning algorithms (e.g., a [24,12,6,4] node, back-propagation neural network and a 24 feature, 4 class, 100 tree, random decision forest using the ALGLIB statistical library (Bochkanov, 2017) with N=14,617 student marking period grade histories from several school districts. These histories were fitted by smooth Bezier curves evaluated at 24 equally spaced points. These student performance trajectories were then hand-classified as: (1) Successful, (2) At-Risk Falling, (3) At-Risk Rising, or (4) At-Risk Failing. Once trained by supervised learning and validated at 98% accuracy, either solution can be used to classify a student performance trajectory from any starting point to any ending point in that student's grade history (Table 1).

RESULTS

Our objective here is to demonstrate how predictive analytics and innovative data visualization techniques, when combined with longitudinal SIS data, can produce powerful decision-making aids for educators and school administrators. Here we focus on applications rather than methodologies. Our examples include: (1) empirical data dashboards for academic advising and support services, (2) use of cohort analysis and longitudinal methods for evaluating educational interventions, and (3) whole school or district longitudinal performance visualizations.

Student Academic Performance Dashboards

Dashboards showing student grade histories and status classification points can be useful visualizations for identifying students who appear to be doing well or to be at-risk in particular or general course content areas. Student progress in the past and during the current school year can provide teachers, advisors, and academic coaches with empirical information for action-oriented decision making and timely educational intervention at the individual level.

We show several different student dashboards in Figure 1, while also demonstrating the use of Bezier curves to smooth raw grading data into academic performance trajectories in specific as well as aggregated course subject areas. In addition, we show how a school can group and visualize the academic histories of an incoming grade-level cohort of students – e.g., the 12th grade incoming class at a large urban high school. In so doing, educators can identify students who individually might benefit by receiving extra support services in their final year to avoid failure and graduate successfully (Lacefield, et.al., 2012)

Cohort Analysis for Evaluating Educational Interventions

In Figure 2 we borrow from our previous research (Zeller, et.al., 2013) to demonstrate how SIS data and predictive analytics can be used to evaluate school interventions in a longitudinal cohort design. A graduation coaching intervention for students identified as At-Risk entering 9th grade was implemented in a rural school district in 2010. All core course performance histories through 8th grade for all incoming students were examined, leading to the identification of N=30 students who appeared At-Risk (treatment group) entering 9th grade. Those students participated in the graduation coaching intervention. We similarly analyzed data from three earlier student cohorts entering 9th grade in 2007, 2008, and 2009, identifying N=127 students also classified as at-risk but did not receive graduation coaching (control group). Subsequent outcome data for the two At-Risk student groups were compared using a longitudinal statistical model. Means plots and significant statistical results comparing academic performance trajectories clearly showed the benefit of graduation coaching for At-Risk student groups.

Longitudinal Multiple-Cohort School and School District Performance Visualizations

Having 10 years of SIS data for all students from point of entry into a district to point of graduation or disappearance and being able to classify students' academic performances in content areas at any time point during their in-district schooling experiences allows a cohort visualization model of the district over time. In our data, most students who were enrolled in the 8th grade in the years 2004 through 2008 had performance trajectories beginning in district middle schools and ending upon graduation or departure from district high schools.

In Figure 3 we show how SIS data can be used to model and profile individual schools and/or whole school districts in terms of student academic performance from admittance to graduation or departure across multi-cohorts and multi-year time windows. We show two different districts (large urban and small rural) in terms of how middle school students with different risk profiles go on to perform in their high schools.

We also can visually explore hypotheses such as "To what degree is middle school success in Language Arts pre-requisite for success in high school Science subjects?" Figure 3-C shows a definite association (also noticed in other STEM subject areas).

Indicators of Stationary School Climate for Student Academic Performance

For each student at every point from entry into a district to graduation or disappearance, that student's particular performance as measured by class grades and teacher judgments occurs in a socio-educational context comprised, among other factors, of fellow students' performances at those time points. If student status can be estimated by point classifications and those classifications expected to have predictive validity in the absence of intervening factors (such as deliberate interventions), this "static" curricular context needs to be taken into account. A step in that direction can be seen in the "status heat maps" that characterize school districts shown in Figure 4.

For example, in Figure 4-A, a large urban district had several middle schools feeding a central high school. Data from 5 student cohorts (2004-2008) is presented. The graph shows a "heatmap" describing the environment or "context" students found themselves within at each time point from middle school entry to high school graduation.

Each vertical "bin" represents an average GPA range in all core courses. The height of each bin reflects the number of students falling into that bin at that time point in their curriculum. The color reflects a weighted combination of the current Status classifications of students in each bin based on their data prior to and including that Status Estimation Point.

In 6th and 7th grade, students with GPAs above 2.0 generally were classified Successful. Students with lower GPAs were mostly Falling or beginning to Fail.

In 8th and 9th grade, some At-Risk students were consistently Failing. However, others with somewhat higher current GPAs were Rising.

10th and 11th grade was a time when many At-Risk students left the school district, while those that stayed were experiencing Falling grades.

By 12th grade, most students were being classified as Successful or Rising.

Figures 4-C and 4-D show that the longitudinal classroom climate differed substantially for students who entered high school classified as Successful compared with those who were classified as At-Risk.

A second example, shown in Figure 4-B, depicts a small rural district where students experience a somewhat different classroom climate. In middle school, many students initially At-Risk were Rising. Transition into high school appears more difficult for many students who began to Fall, some to the point of Failing. Still, a much higher proportion of these students remained in school and most were either Successful or Rising at the point of graduation.

The degree to which such stationary maps (e.g., 5 years of full 8th grade student cohorts passing though the 6th-12th grade curriculum) differ by student academic performance status, by school or school district, and by course content area is surprising and a promising subject for future research. These maps reflect the contexts in which expectations for students are formed.

On the other hand, it would not be difficult to use a cohort GLM model and examine statistically whether and/or how a district school climate might be changing over time. One also, of course, could statistically compare schools or whole districts cross-sectionally and longitudinally if desired. Few school agencies that assess school and district “performance” have the tools to do that sort of thing at present.

SCIENTIFIC OR SCHOLARLY SIGNIFICANCE

In the past it has not been feasible for schools and school districts to gather, analyze, and visualize student record information the way we have described in this paper. Few if any of the SIS platforms we are familiar with provide predictive analytics help to school administrators beyond basic data collection and standard report generating functions. School and district level performance visualizations are rudimentary; typically, cross-sectional views, perhaps disaggregated by categorical variables. Thus, individualized data-driven decision-making is actually quite rare.

Today, tools and methodologies are available to harvest the rich information gathered in a SIS. Furthermore, in more and more places, school SIS data is being uploaded and aggregated at the district, regional, or state-level (CEPI, 2010). Resources and data analytics are available for improving our understanding of student learning outcomes, evaluating the effectiveness of educational interventions, and modeling school and school district performance for quality control and system change purposes.

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Applegate, EB & Lacefield, WE (Nov, 2011) Analytical basis for modeling of student performance data: Validity, automation, updating, and interactive evaluation processes. Multi-paper session: Data feedback loops in educational: Intervention process and student progress monitoring data visualization tools and procedures. AEA, Anaheim, CA.

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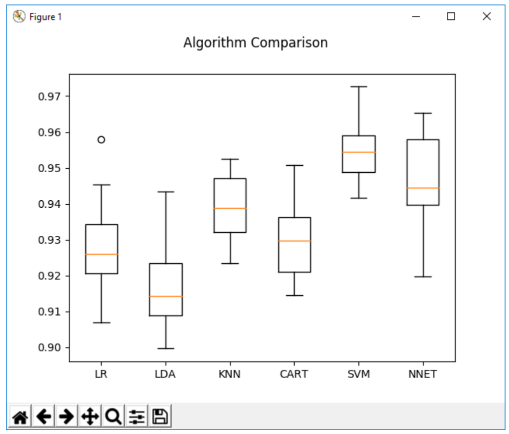
FIGURES AND TABLES

Table 1: Machine Learning Models and Training Statistics

<u>Feature</u> variables were 24 equally spaced time points, including starting and ending points, representing a Bezier curve academic performance trajectory. The classification or <u>Label</u> variable, Status (i.e., the shape of each trajectory), was coded: *(1) Successful, (2) At-Risk Falling, (3) At-Risk Rising, or (4) At-Risk Failing.* Several real and Monte Carlo datasets with 14,617 and 10,640 labeled cases respectively were examined, using multiple models and methods, with 60% of the data for training and 40% for model mini-batch validation and batch testing.

Models	**Methods**
• Logistic Regr.	• TensorFlow
• Discrim. Analysis	• KERAS-SciKit
• KNN	• MS CNTK
• Decision Trees	• ALGLIB C#
• SVM	
• 24:12:6:4 NN+BP	



MS CNTK for C# Mini-Batch Training/Validation (98%)

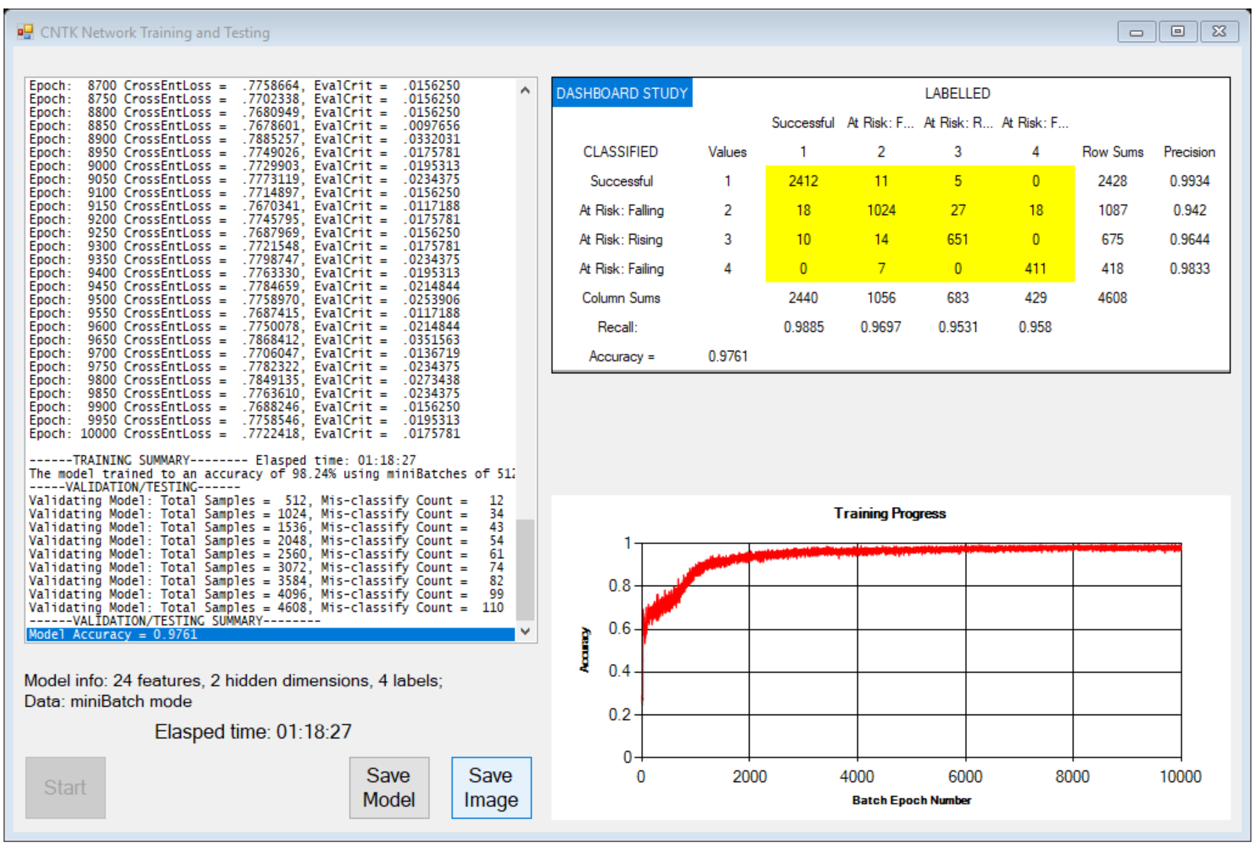


Figure 1: Example Student Dashboards

Figure 1-A shows a student classified as “Successful” in all core courses entering the 8th grade in middle school and continuing to succeed through the 8th, 9th, and 10th grades.

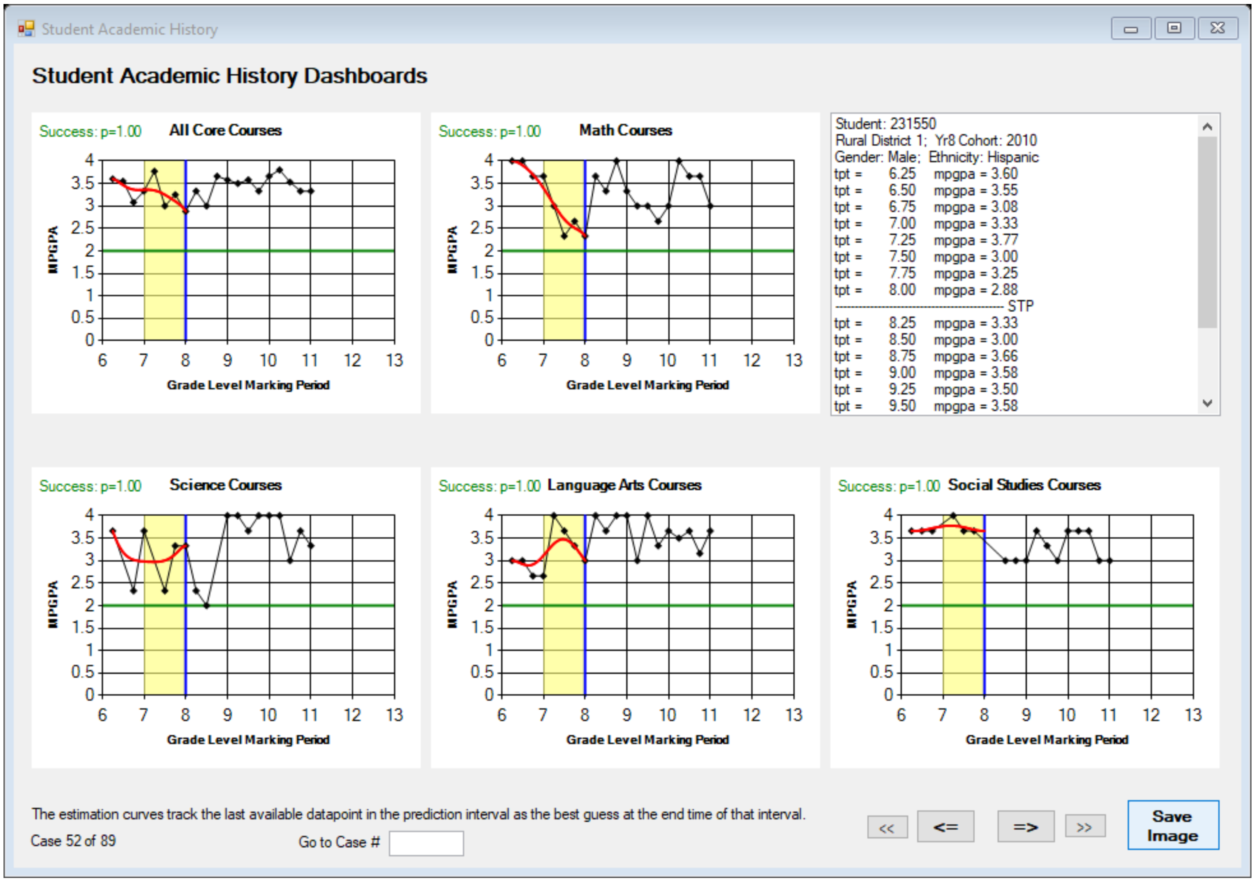


Figure 1-B shows a student classified as "At-Risk Falling" in all core courses entering the 8th grade in middle school. This student had been doing well in Language Arts courses and Social Studies but not in Math or Science courses. Her future did not turn out well in high school, at least up to the middle of 10th grade.

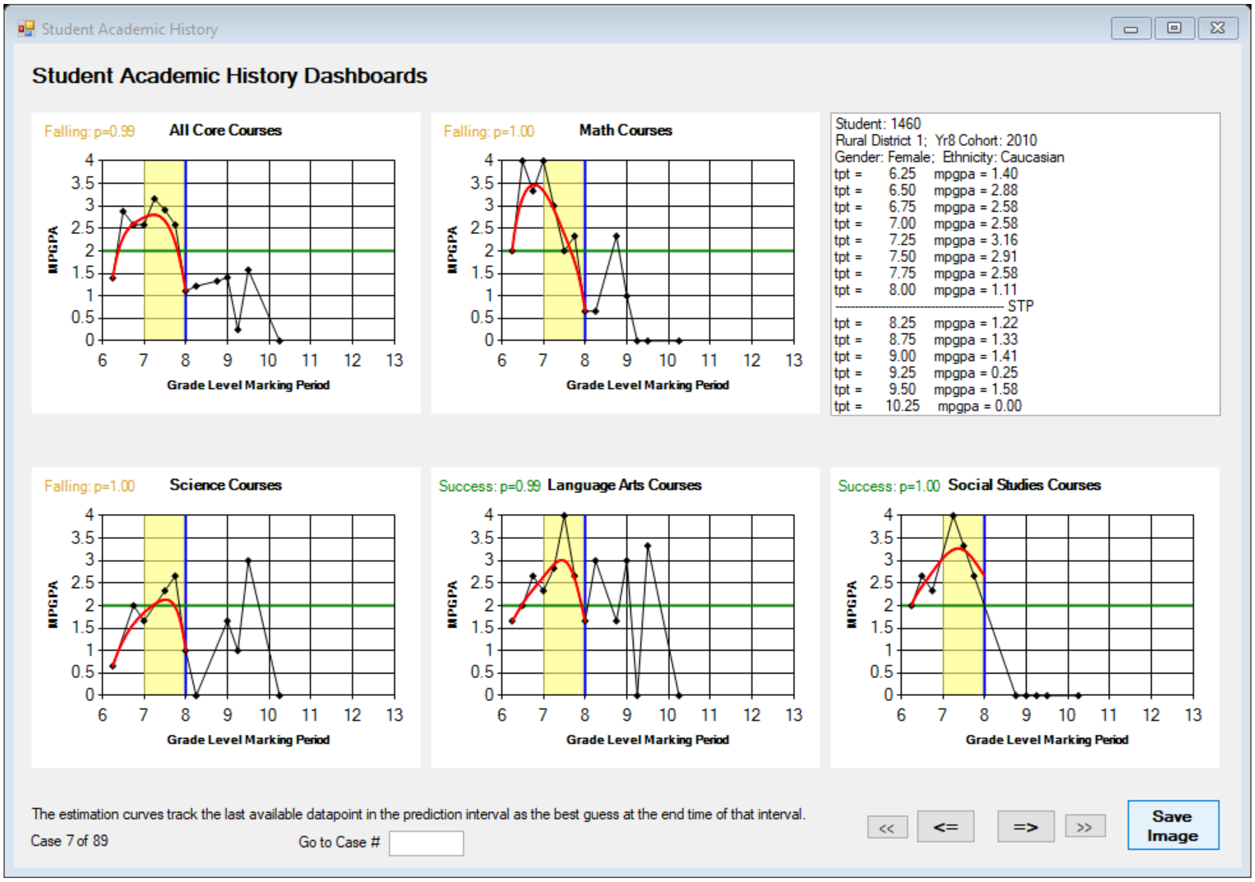


Figure 1-C shows a third student who was classified as “Successful” in all core courses entering the 8th grade in middle school. This student went on to do very well in 8th grade but eventually encountered difficulties in high school, particularly in Math courses.

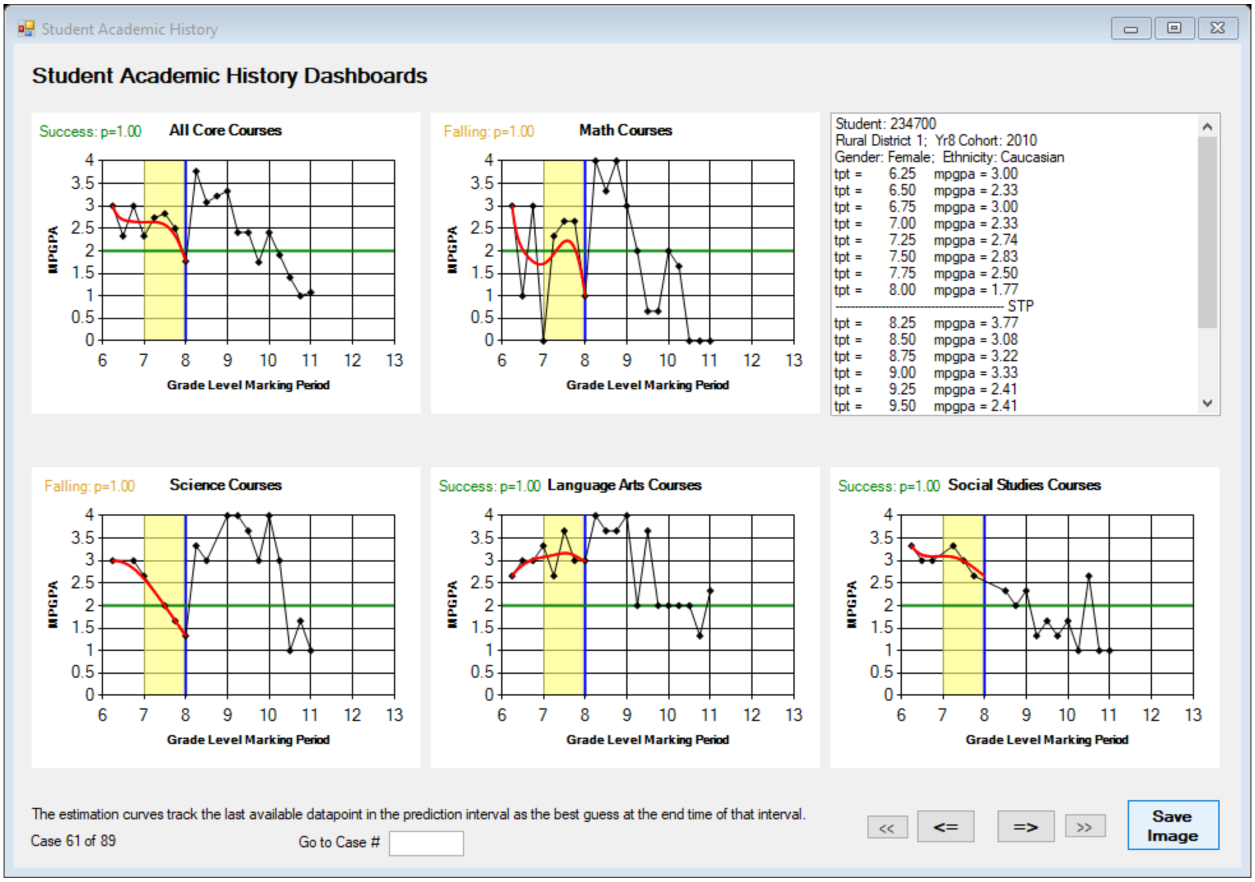


Figure 1-D shows a summary by status classification in all core courses for the entire incoming cohort entering the 12th grade in a large urban high school in 2011 (Lacefield, W.E., et.al., 2012). According to the source:

> "… patterns for the incoming 12th grade students, almost all of whom will shortly graduate and enter the competitive job market or post-secondary education world. … **Successful** students continue to succeed. **At-Risk: Falling** 12th grade students really have not fallen very far. Some students really have begun to **fail** almost entirely in the past year. But the **Rising** students appear very similar to the newly **Failing** students, until 11th grade when something happened in their lives to turn that performance around. What was that? Why did only a portion of the students who were failing do that? How can this newly won success be sustained until graduation and beyond? These are fundamental questions for individualizing pedagogy."

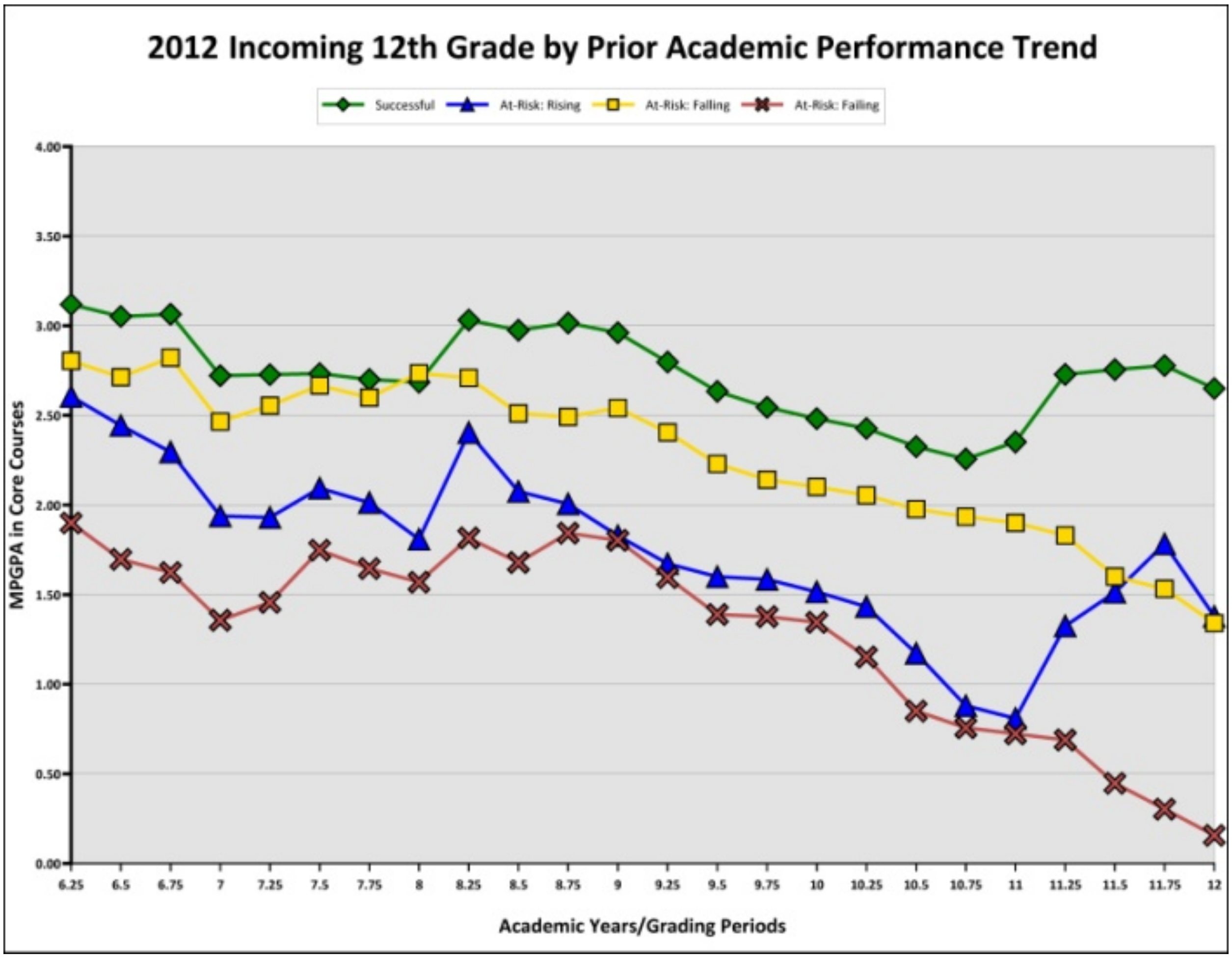


Figure 1-E shows the same data re-analyzed using Bezier curve smoothing rather than raw student data.

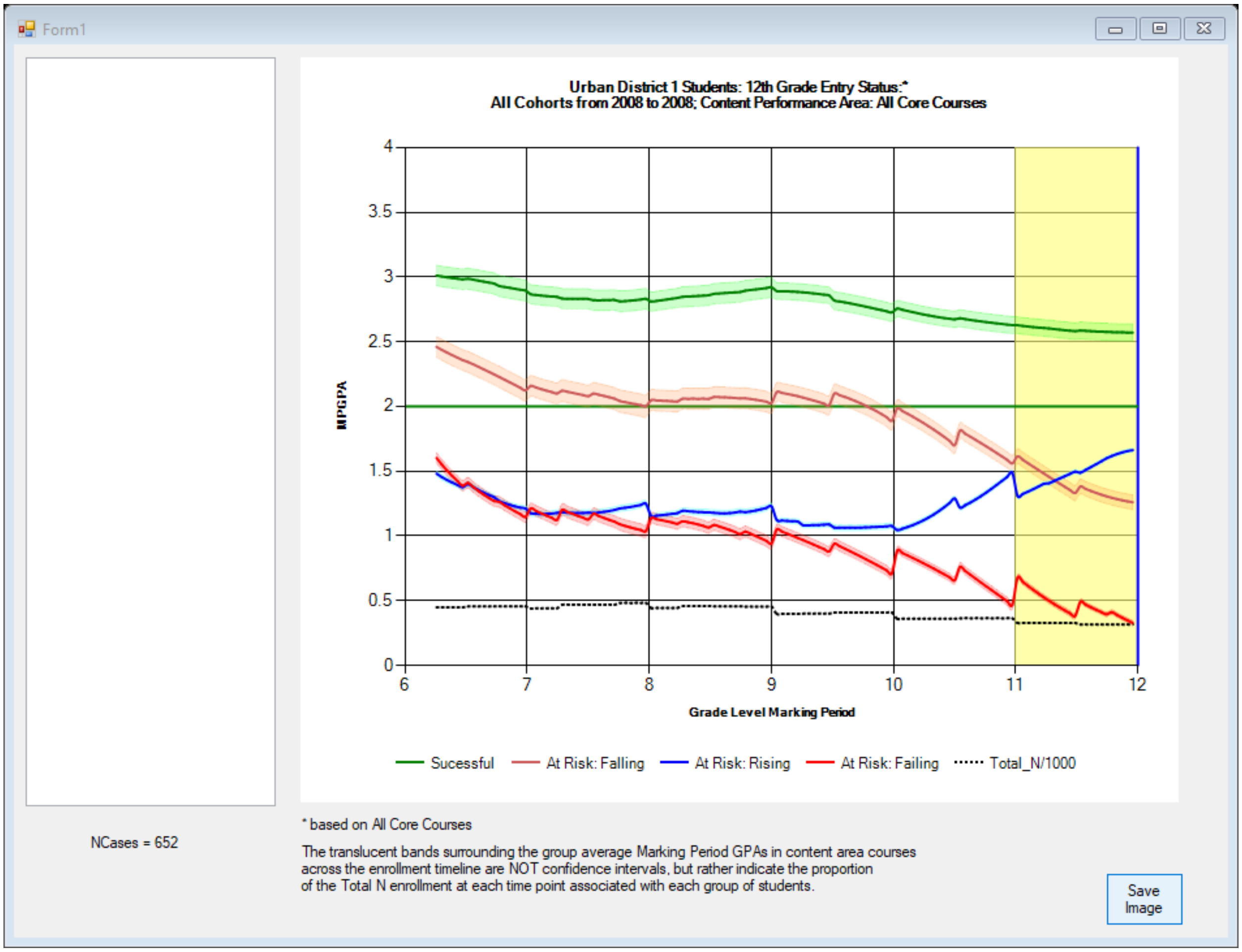
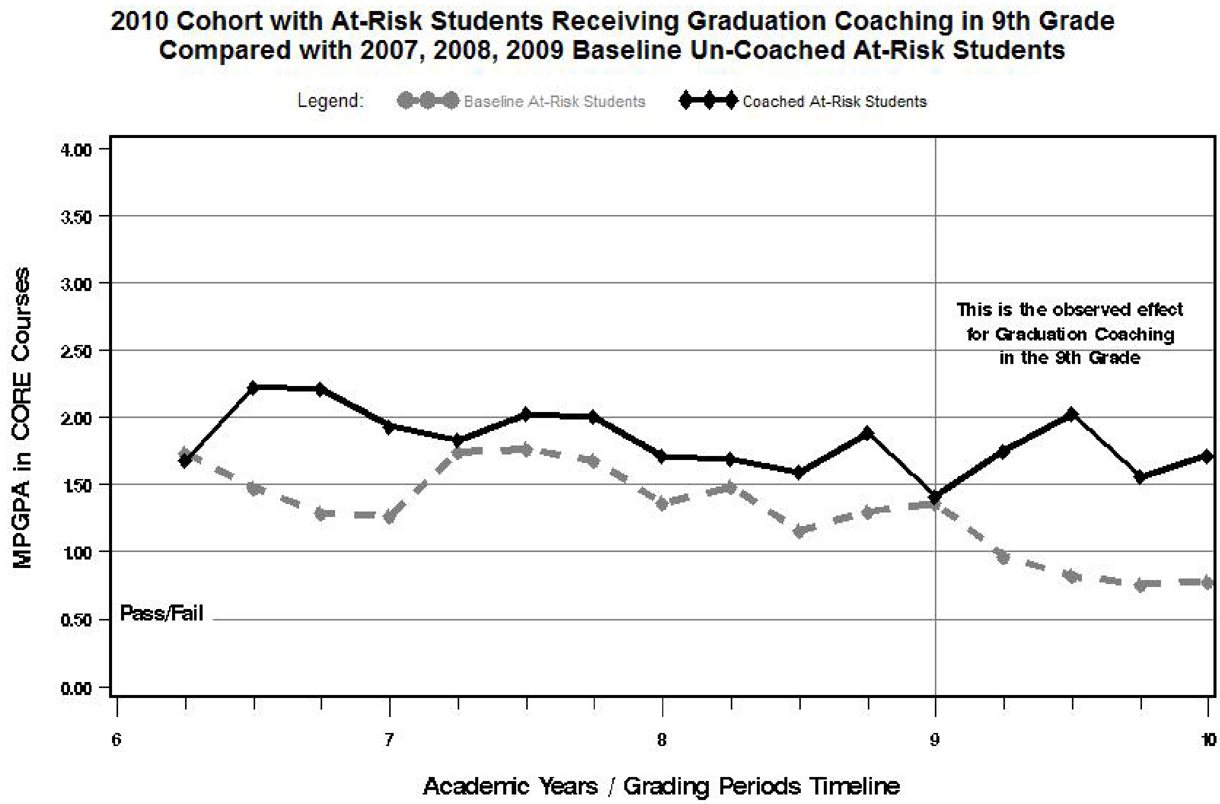
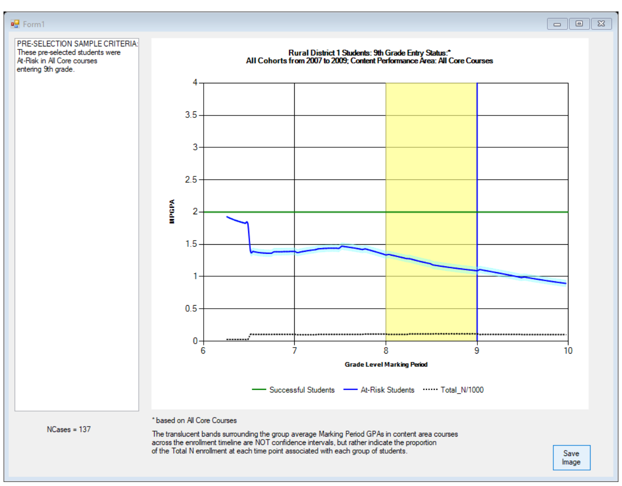


Figure 2: Using Student Information System Data and Predictive Analytics to Evaluate School Interventions (Zeller, P.J., et.al., 2012).



Using Bezier Curve Smoothing

Baseline Un-Coached At-Risk Students | **Graduation Coached At-Risk Students**



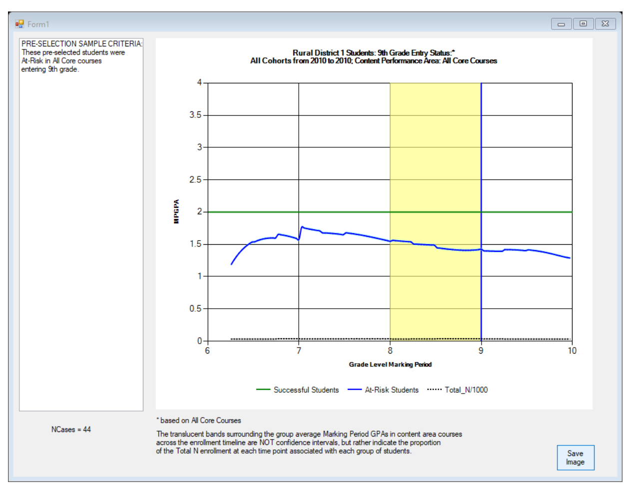
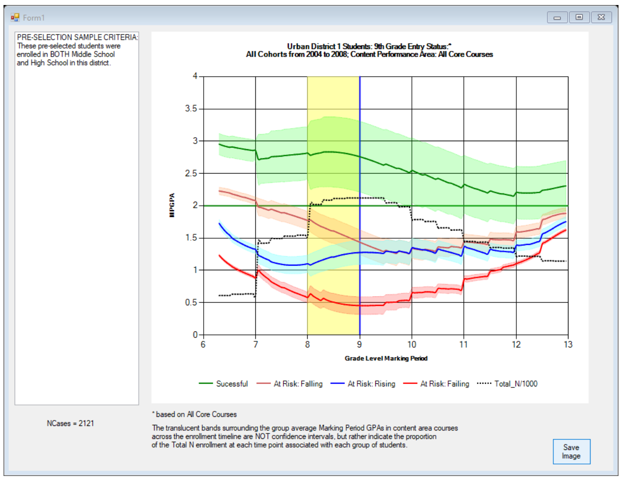


Figure 3: Individual Schools and Entire School Districts Can Be Modelled and Profiled Using SIS Data.

Figure 3-A is an example of a large urban school district with several middle schools feeding a high school. Students in 5 consecutive cohorts are grouped by their status classification as would be known at the point of 9th grade entry. Each group is then followed through their futures in high school in terms of all-core course performance and, for example, math course performance. These school districts experienced an attrition rate (due somewhat to transfer out but mostly to drop-out) in high school above 50%.

All Core Courses



Math Courses

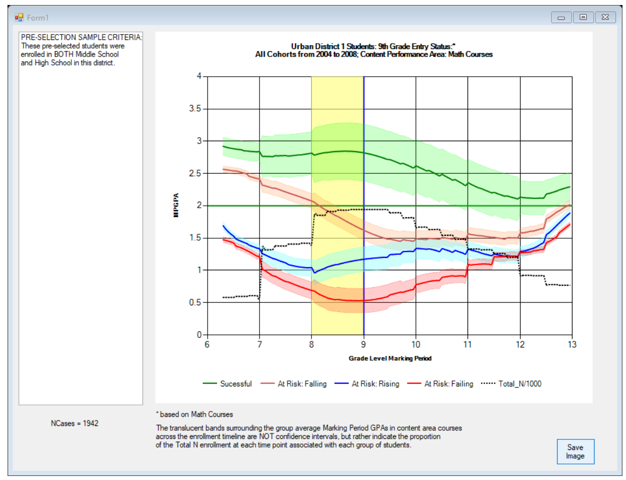
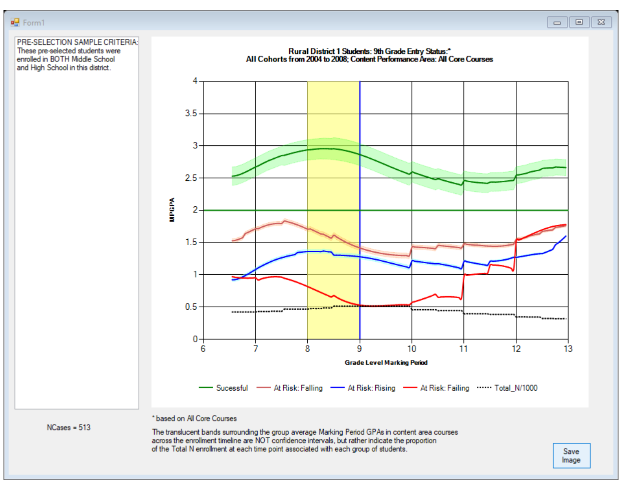


Figure 3-B is an example of 5 consecutive student cohorts in a small rural school district with one middle school feeding a high school.

All Core Courses



Math Courses

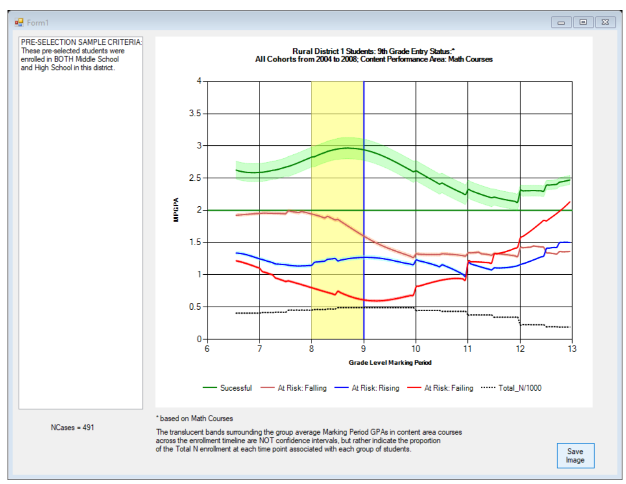
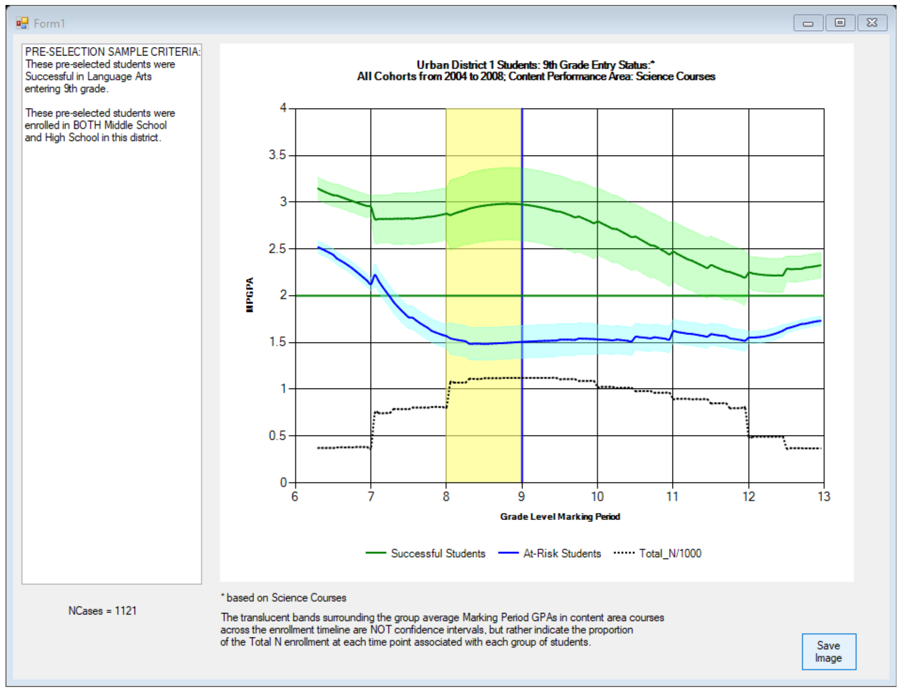


Figure 3-C visually explores the relationship between middle school success in Language Arts and success in high school Science subjects, again using 5 consecutive student cohorts. Few students did well in Science in middle school while also being at-risk in Language Arts, but those students (who remained in school) did far less well in science courses in high school than their peers with adequate preparation in language arts skills in middle school. (This pattern appears in other STEM subjects as well.)

Students Successful In Middle School Language Arts



Students At-Risk In Middle School Language Arts

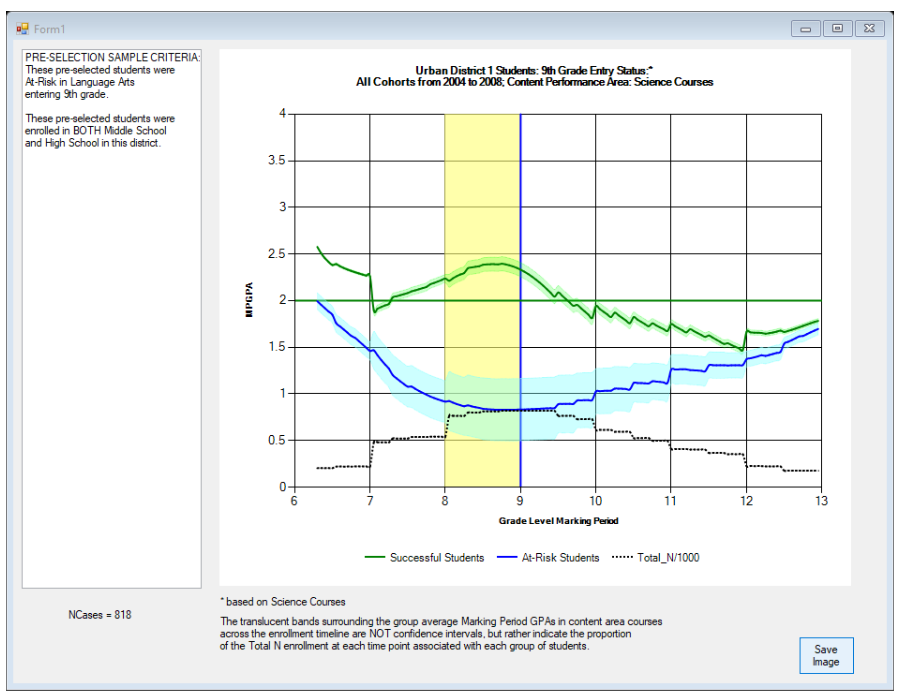


Figure 4: The Context for Student Academic Performance in Public Schools

Figure 4-A is an example of a large urban school district with several middle schools feeding a high school. Five consecutive student cohorts are grouped into bins by their moment-to-moment academic performance as measured by estimated all-core GPA following their trajectories up to each moment. Their status classification as would then be known at each moment as typical futures unwind is reflected by the bin colors.

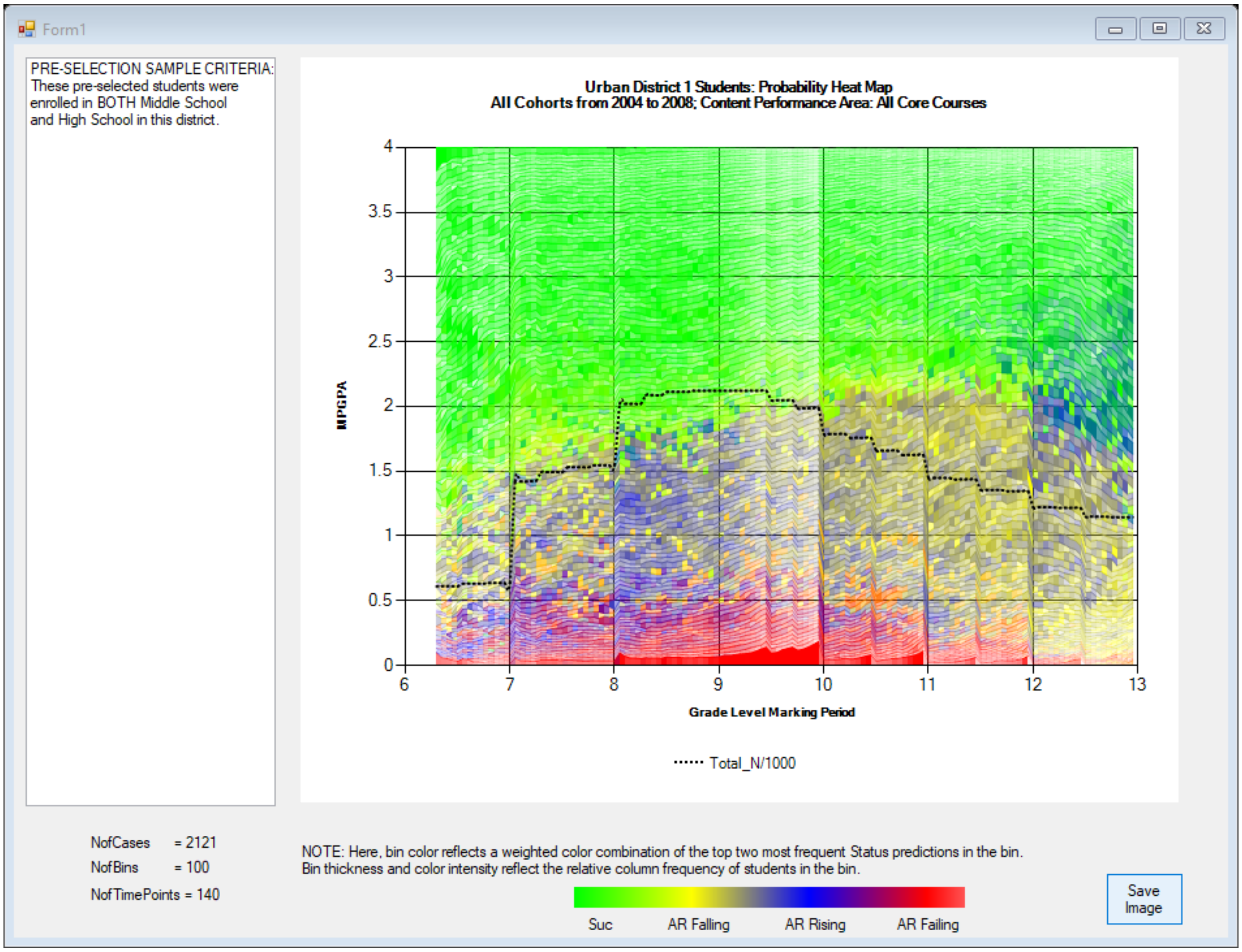
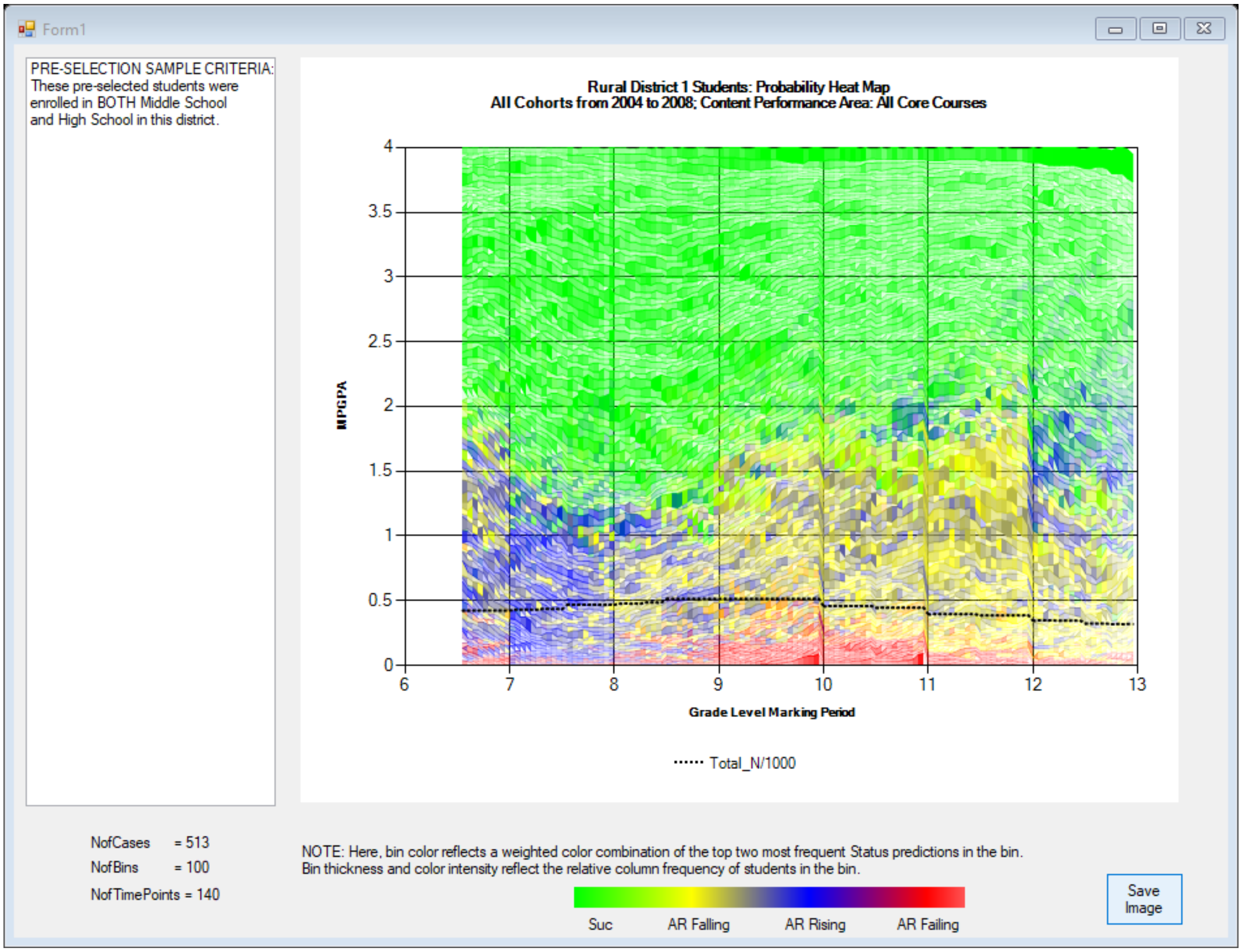


Figure 4-B is a similar example of 5 consecutive student cohorts in a small rural school district with one middle school feeding a high school.



Figures 4-C and 4-D return to the example of a large urban school district with several middle schools feeding a high school. Here in 4-C, among the 2122 students in the 5-cohort sample, we see the how the contextual pattern looked in the past in middle school and in the future in high school for a subset of 1104 students who were classified as "Successful" at the point of high school entry. And we also can see the shape of that pattern for the other 1018 students who were classified as "At-Risk" in Core courses at entry into high school. These maps reflect the context in which expectations are formed.

Figure 4-C: Successful Students

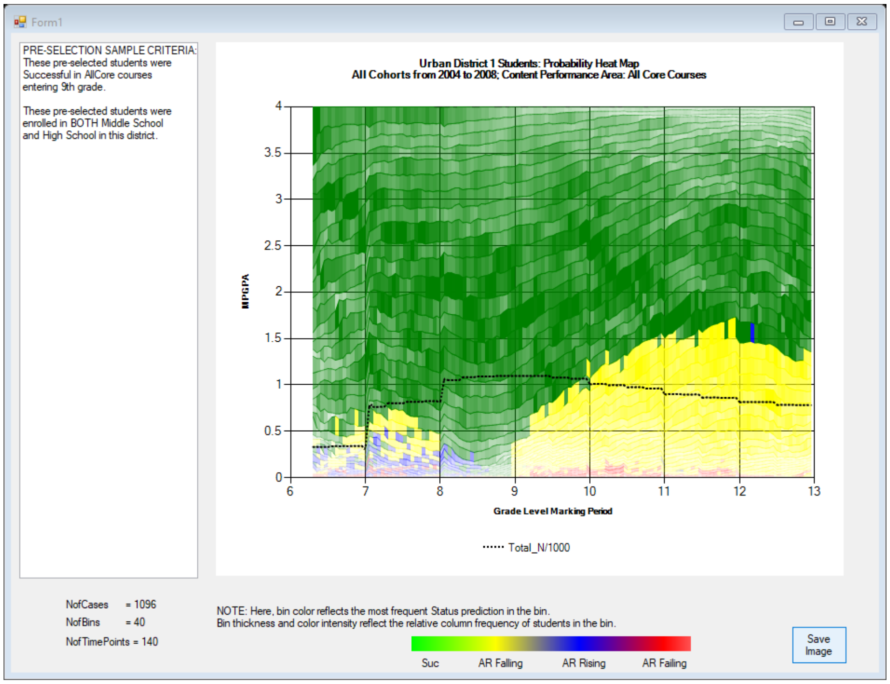


Figure 4-D: At-Risk Students