The Data Cabinet: A platform for collecting and using whole-person data to improve learning outcome predictions and inform the selection of interventions

MARi is an intelligent mentorship technology platform that integrates whole-person data from a myriad of digital sources and uses it to provide personalized recommendations and resources to help close the skill gaps standing between learners and their academic and career goals. For K-12 school districts, these data sources include learning management systems, formative and summative assessments, other commercial tutoring systems, and students and teachers themselves.

The Data Cabinet is one of MARi's features that was developed in collaboration with K-12 administrators and teachers and is heavily used by our K-12 schools. The Data Cabinet is a spreadsheet-like dashboard that comprehensively displays all academic and whole-person data that the school collects on each student. Many data ingestion capabilities are automated, making this feature readily scalable and applicable to new schools. Our teachers and administrators use the Data Cabinet regularly view, synthesize, discuss, and add to the student data when they have meetings to discuss learning/behavioral issues and interventions.

Figure 1. Example user interface for an academic data cabinet.

Importantly, the Data Cabinet provides a way to focus just as much on the importance of whole-person, meta-academic attributes of a student as their academic performance. In 2016, G. J. "Russ" Whitehurst, the former director of the United States Institute of Education Sciences and the current chair and director of Education at the Brookings Institution, argued for the importance of measuring and developing so-called "soft skills" – or "personal qualities, other than formal academic knowledge transmitted by schools, that affect student adjustment" – in K-12 education.

MARi can build custom data pipelines to connect into any source of digital data relevant to students' academic and career success. Some examples of sources for which MARi has pre-built ingestion pipelines, include:

- State standardized assessment data
  e.g., Virginia Standards of Learning exams, exported from Pearson
- Student grades
  Automatically pulled from the Student Information System (SIS), via API if possible
- Attendance data
  Automatically pulled from the Student Information System (SIS), via API if possible
- Discipline data
  Automatically pulled from the Student Information System (SIS), via API if possible
- Powerschool Assessments' formative assessments
  e.g., Benchmarks, Student Growth Assessments, Exams
- Renaissance Learning's STAR Math, Reading formative assessments
- Scholastic Reading Inventory (SRI) formative assessments
- iReady Math, ELA student activities & assessments
- Positive Behavioral Interventions & Supports (PBIS) data
- Custom administrator/teacher inputted data – directly in the Data Cabinet Interface
  Some of our schools use this feature to tier students, collect notes/ratings on whole-person qualities that may relate to academic success, including issues with motivation, attention/focus, attendance, and social factors. They also use the feature to track students' interventions, services, and after-school activities.

The Data Cabinet is currently being used in multiple school districts in Virginia. The teachers who are actively using the MARi Data Cabinet on a daily basis have reported that it has saved them countless hours of manual data entry by automatically ingesting data from either APIs, or machine-readable files. They have also reported that the dashboard has made it much easier for them to organize, filter, and visualize the data to easily understand their students' progress and needs. There are plans to collect formal survey data on the impact it has had on teachers' experiences working with student data.

A preliminary analysis sought to investigate whether strictly meta-academic data improved a model's ability to predict whether or not students passed their mathematics state standardized test outcomes for the current 2018-2019 school year. The scope of the preliminary findings presented here include approximately 350 students' data from one middle school in Virginia spanning grades 4-8. The "academic" predictor variables included previous years' state standardized assessment result for the same subject, student grade averages from the current school year, and three different formative assessments from the present school year. The whole-person predictor variables included attendance (absence/tardy/leave early counts), teacher coded information on students' motivation, attention/focus, and discipline/behavior, and standardized assessments of reading level.

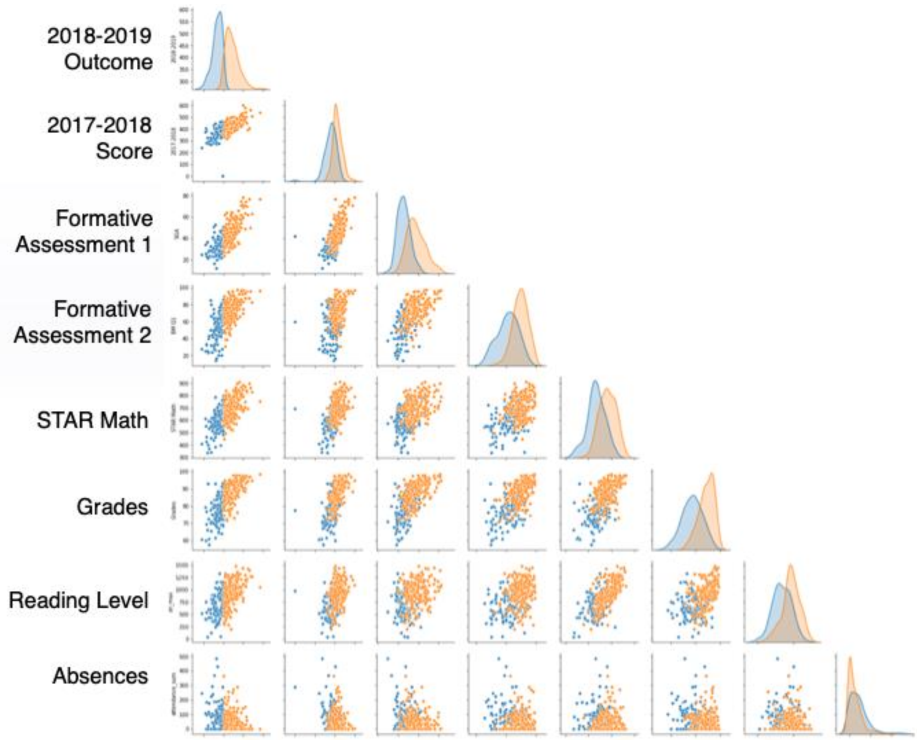

Figure 2. Pairwise scatterplots for each continuously valued feature (every feature except teacher-coded information, which was discretely valued), as well as the distributions of the feature values for those who passed (orange) and did not pass (blue).

Logistic regression (with L1 regularization for feature selection) and random forest classifiers were applied using (1) only the academic predictor variables, (2) all whole-person predictor variables, (3) all whole-person predictor variables and intervention data. For both classifier types, the models that included the whole-person predictor variables performed better than the model that did not, and the model that additionally included intervention data performed best.

	Model 1 Academic Data Only	Model 2 All Whole-Person Data	Model 3 Whole-Person Data + Interventions
L2-Regularized Logistic Regression	82.70%	83.31%	84.58%
Random Forest	82.73%	83.81%	83.77%

Figure 3. Mean predictive accuracies of based on fitting each predictive model to repeated, independent train/test splits. Including whole-person data and data on interventions improves the model's ability to predict standardized test outcomes.

Figure 3 shows the feature "weights" resulting from the Logistic Regression Model 2, reflecting each feature's contributions in predicting Virginia SOL Pass/Fail for the mathematics exam. Of the variables that were not domain-specific, the strongest predictor was reading level, followed by attendance.

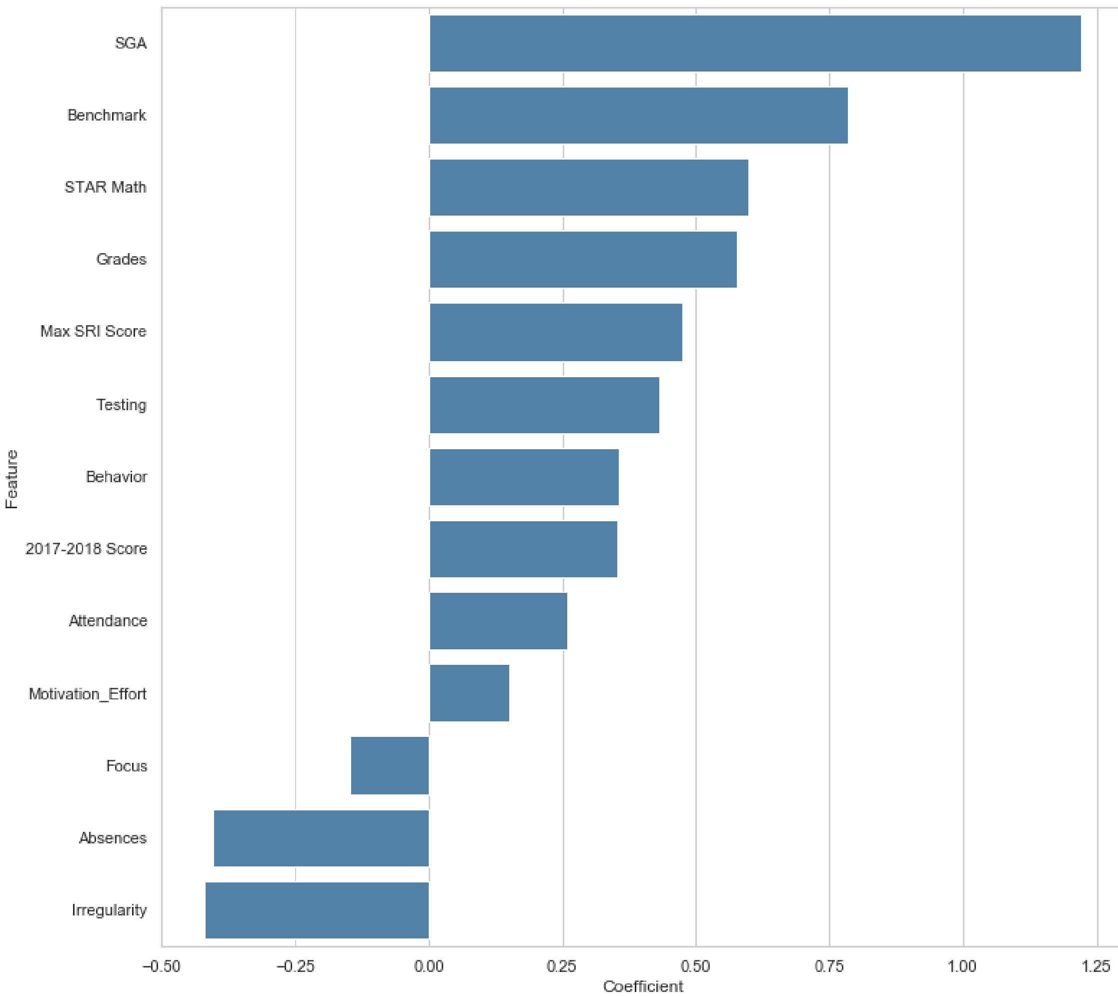

Figure 4. Feature weights towards predicting 2018-2019 Virginia SOL Pass/Fail status. Derived from the Logistic Regression Model 2 fitted to data. Note: "Absences" refers to the continuous Absence count provided for every student from the SIS data, whereas "Attendance" refers to a discrete flag that some teachers placed on certain students with perceived attendance issues.

Figure 4 shows the feature "weights" resulting from the Logistic Regression Model 3, reflecting each feature's contributions in predicting Virginia SOL Pass/Fail for the mathematics exam, including interventions. Preliminary analyses showed that two specific type of interventions called "Expanded Core Tutoring" and "Volunteer Tutoring" positively predict standardized assessment outcomes. In particular, "Expanded Core Tutoring" had a higher coefficient estimate than several academic predictors (one math-specific formative assessment, and the state assessment results from the prior year).

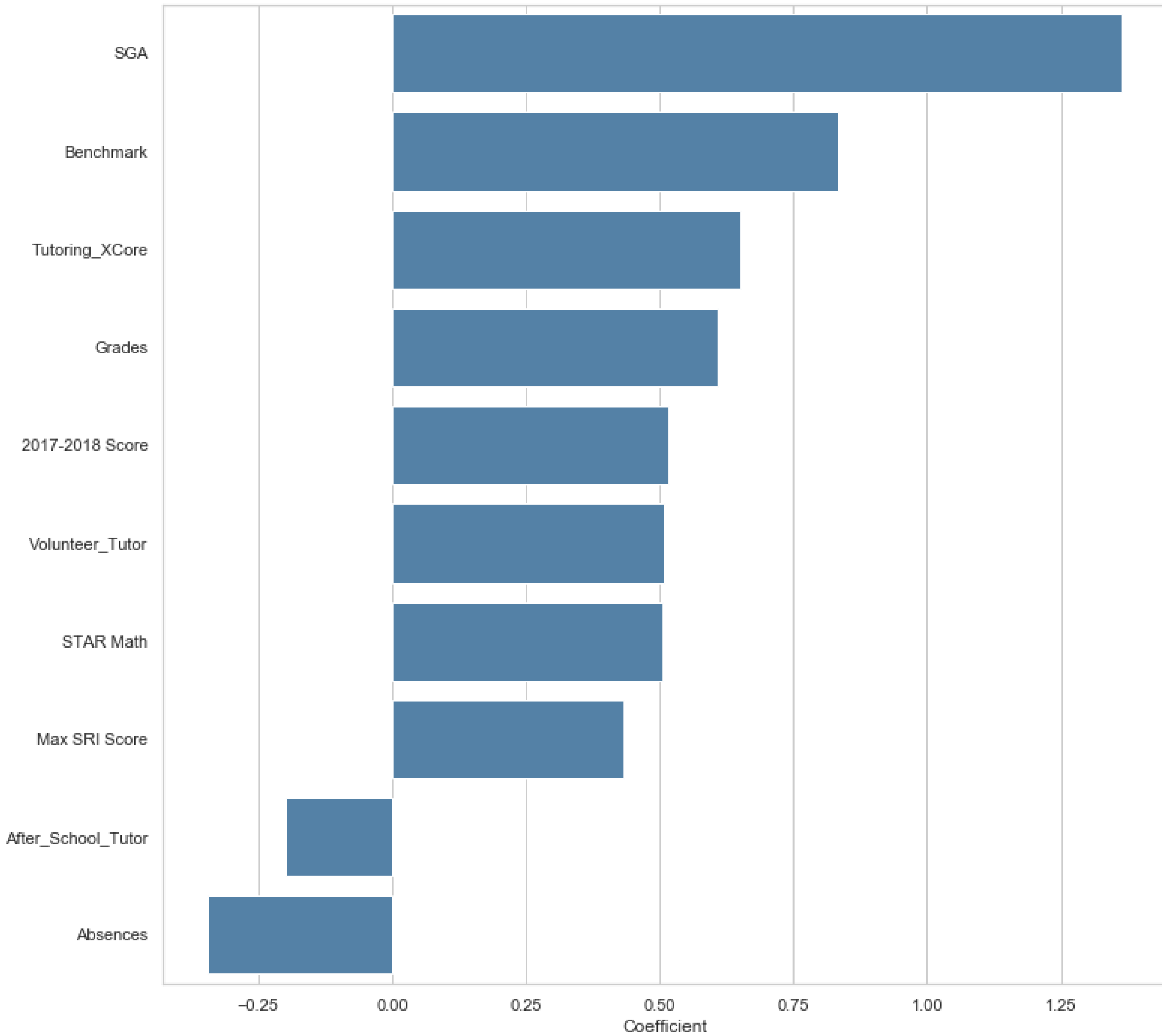

Figure 5. Feature weights towards predicting 2018-2019 Virginia SOL Pass/Fail status. Derived from the Logistic Regression Model 3 fitted to data, showing the relationship between different interventions and test outcomes. Of the three types of interventions, the "Tutoring_XCore" intervention had the greatest positive relationship with passing the mathematics SOL exam.

Beyond these preliminary analyses, the rich longitudinal data that is collected in the Data Cabinet (spanning many years of each student's time in school)—including information on which interventions were delivered to which students—creates the potential to use data mining/modeling techniques to infer the relative effectiveness of different interventions and services. The teachers and administrators using the platform have expressed enthusiasm for understanding these types of insights, and we plan to pursue these analyses in future work.

