Empowering Teachers with Big Data Analytics

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Outline

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Our Adaptive Learning Platform (ALP)

ALP is a cloud-based data management, assessment, and reporting platform that uses machine learning to combine and give meaning to data from a variety of learning contexts.

ALP's Learner Model

MACHINE LEARNING
ALP comparison data from other learners

PHYSICAL CONTEXTS
Parent/teacher input about offline activities: individual work/play, group projects, etc.

DIGITAL CONTEXTS
Behavioral measurements from online activities: apps, games, smart devices, wearables, etc.

ALP is designed to create a universal, longitudinal, high-dimensional psychometric profile of a learner. Our learner model can work across contexts and across ecosystems to ensure that students are optimally engaged wherever and whenever they are learning.

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Learning Analytics

- Learning analytics deciphers massive amounts of data generated in different learning contexts.
  - Assess students' academic progress,
  - Predict their future performance,
  - Identify potential problems
- For teachers:
  - provide more targeted teaching interventions for students

After School Learning Program

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After School Learning

- Event data as learners interact with a tablet with curricular content from a Korean partner's educational system.
- > 200,000 learners in math, Korean, social studies and science, following the Korean national curriculum.
- Students in the program mostly work at home and are visited by a teacher once a week.
- The content is arranged in weekly topics with small content blocks containing lectures and practice questions.
- Each week ends with a test.
- As the learners progress through the curriculum, they watch lectures, answer anywhere from 50 to 100 practice questions, and answer a test with 10–20 questions.

Teacher Reports

- Our technology provides teachers with weekly reports that are updated continuously, as well as monthly reports to track the learners' progress over time.
- These reports contain more information than just the correct/incorrect nature of student answers.
- Our cloud-based analytics engine processes millions of data events streaming in, using psychometric models that are regularly being calibrated to construct hundreds of personalized metrics and insights.
- These insights are dynamically prioritized, with the most important passed along to teachers to help all learners reach their full potential.

What do the Reports Contain?

For every weekly unit of the curriculum attempted by a learner, we produce a report for that learner's teacher.

- general behavioral insights,
- specific question-level insights,
- one overall message about the learner's behavior and achievement in the week.

Behaviors

The behaviors analyzed are:

- skipping,
- answering speed (too fast/slow),
- guessing,
- leaving parts of the question blank,
- skipping the next question after getting the previous one wrong,
- retrying/not retrying incorrect questions,
- watching/not watching all lectures, and
- checking/not checking hints after getting a question wrong.

Additional Metrics and Insights

- In addition to these behavior metrics, the reports also include
- question insights based on
  - personalized speed and
  - ability estimates and
  - performance on the weekly test.
- These details empower the teacher to
  - quickly identify questions/concepts each student is struggling with,
  - praise good study habits, and
  - assess student performance not only at a individual level but also in comparison to peers.

Answer Speed

- Learner's expected time on the item given their working speed and whether the learner is answering faster or slower than 90% of the other students answering the item.
- A Bayesian personalized estimate is kept of his or her working speed and updated based on items the student answered correctly,
- The estimate is based on a linear mixed model of the logarithm of the response time, with the learner's working speed estimate calculated relative to the average time intensity of the item for other learners.
- e.g., if the learner's response time is faster than 90% of other learners' response times but this is expected given this learner's working speed, the item is not flagged as too fast.

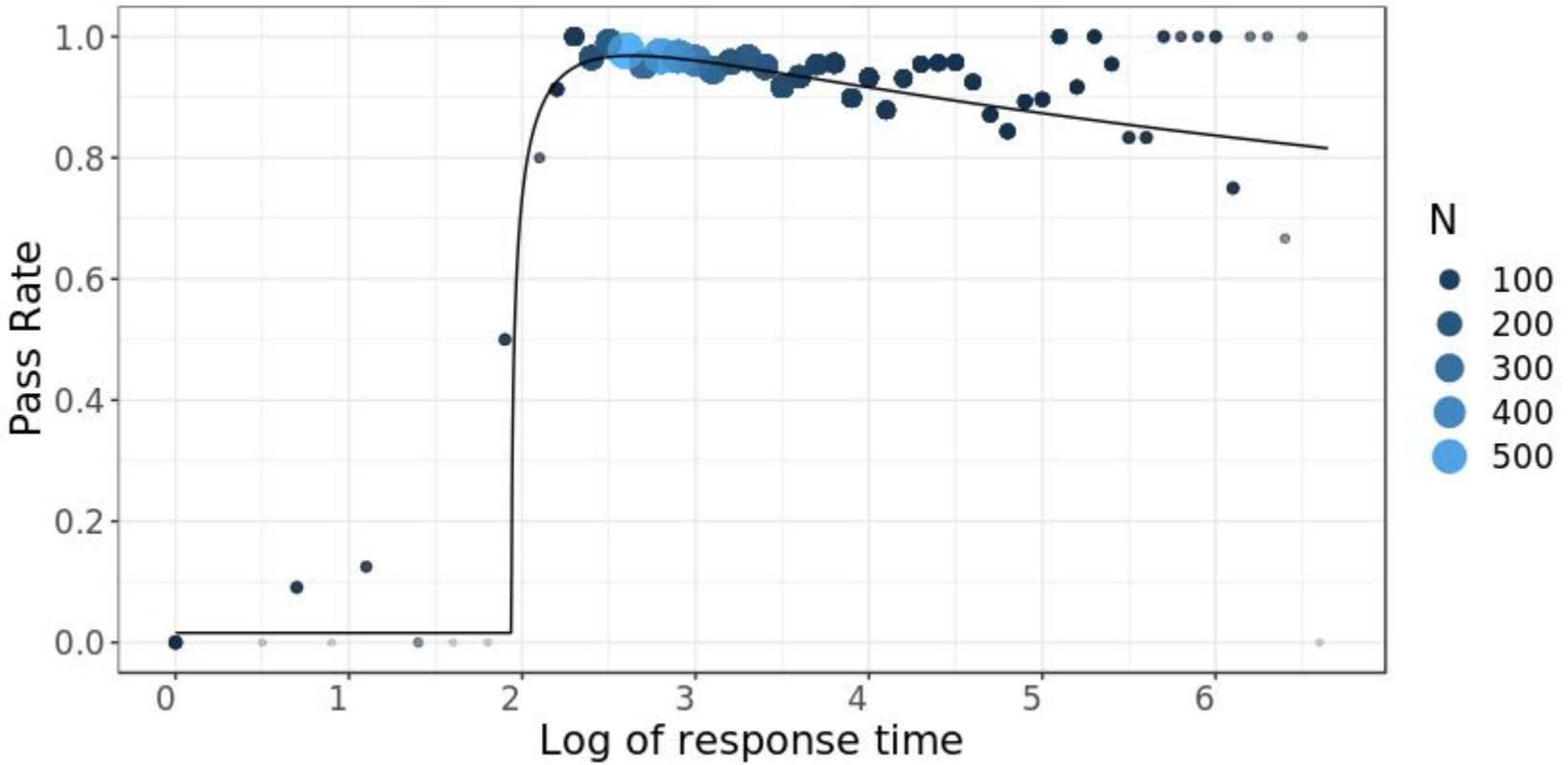
Item Difficulty

- Based on the learner's ability estimate and question difficulty:
  - questions are categorized as hard (<50% probability of getting the question correct),
  - easy (>80% probability of getting the question correct) and
  - medium for a given learner.
- Ability estimates are based on an adjusted version of Bayesian Item Response Theory models (Bock & Mislevy, 1982; Van der Linden & Glas, 2000)
- The final ability estimate and question difficulty estimates represent how well a learner did compared to other learners at the end of that edition.

Guessing

- We developed a general model for estimating thresholds for response times that are short enough to suggest that students probably guessed the answer (Wise & Kong, 2000; Baker et al. 2006)
- Comparing response times to pass-rates, most questions have a region of low response times with low pass-rates and a region of higher response times with higher pass- rates.
- These models have low mean squared error (~0.05) compared to actual response time vs. outcome data.
- We found that our model needed at least 50 correct and 50 incorrect responses to be reliable.

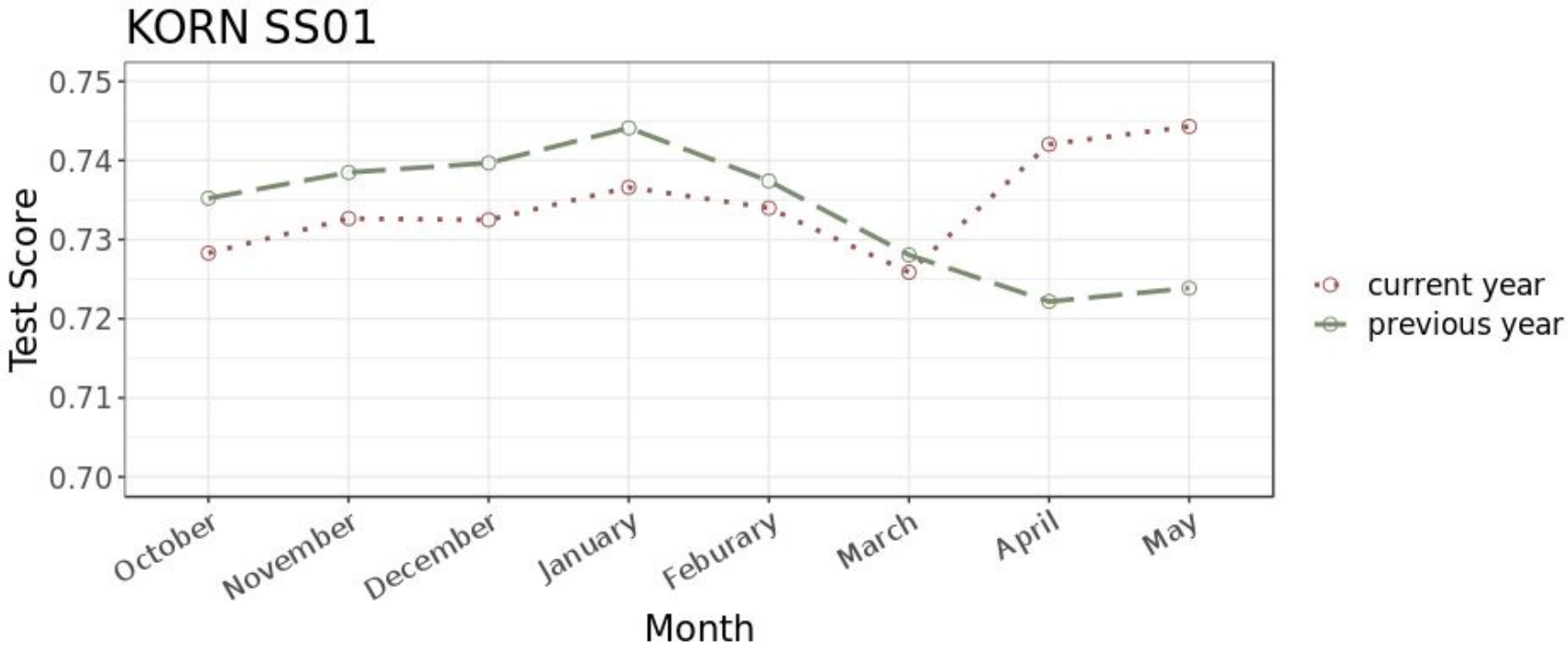
Guessing


Pass Rate
1.0
0.8
0.6
0.4
0.2
0.0
0
1
2
3
4
5
6
Log of response time
N
100
200
300
400
500

Efficacy - comparison with historical data

- We used over 1.2 million individual scores of ~40,000 learners (for the subject Korean).
- In addition to the fixed effects, we also included the random effects to address the variability of the difficulty of material and individual differences in student performance.
- We also controlled for seasonal effects of curriculum.
- Statistically significant, positive interaction effects starting around the fifth month of the data (i.e., at least one month after the implementation of the program),
- Indicates that the test scores relative to last year had shown improvement.

Efficacy - Comparing historical data



Efficacy - Based on Teacher Views

- We compared students whose reports were more frequently vs. less frequently viewed by their teachers.
- The improvement in scores relative to the never viewed group range between 0.52 to 1.69 points
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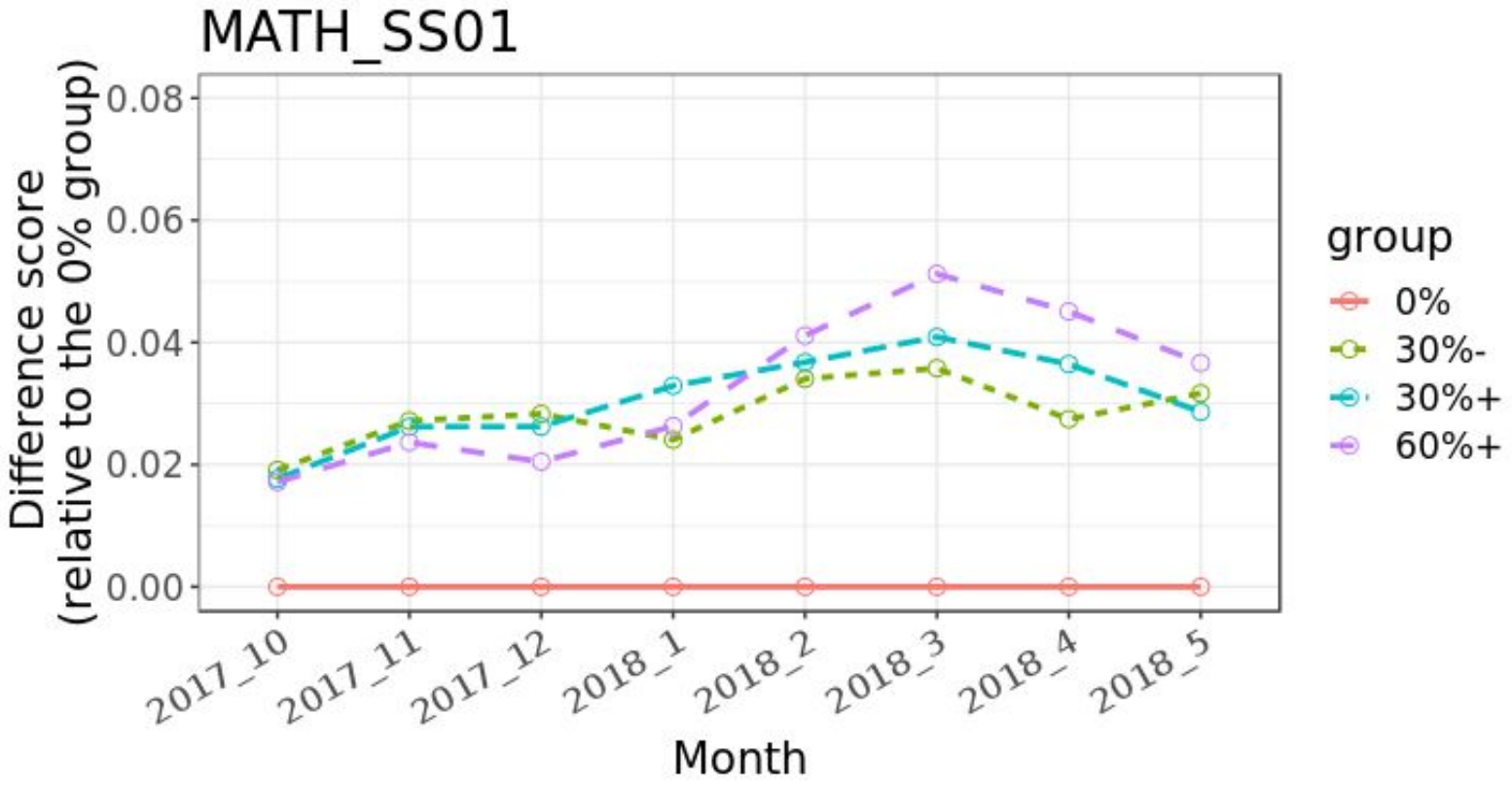
	2018/1	2018/2	2018/3	2018/4	2018/5
< 30%	0.72(*)				
30% - 60%	0.52(.)	0.65(*)	0.73(*)	0.81(**)	0.93(**)
> 60%	0.98(***)	1.12(***)	1.20(***)	1.69(***)	1.40(***)

Efficacy - Based on Teacher Views



Other Features in the reports

- Trends in behavior and achievement
- Score Prediction
- Item Difficulty prediction
- Adaptivity

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Personalized, Lifelong Learning