Learning Analytics: Potential Opportunities for e-Learning in the Workplace

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2020 has been an unusual year so far
Learning looks a little different right now
Before 2020

• There was already an explosion of data becoming available about learners and learning
Before 2020

• There was already an explosion of data becoming available about learners and learning

• As learning needs to move online, the data becoming available increases considerably
Interactive Learning Environments
Two crossover events are very rare.

The largest group is parental since crossovers are uncommon.

The Q and q alleles have interchanged between the parental and SCO genotypes.

The Q and q alleles have interchanged between the parental and DCO genotypes.
We are collecting data...

• What do we do with all that data?

• To benefit students
• To support instructors
We are collecting data...

• What do we do with all that data?

• To benefit students

• To support instructors

• People have been asking that question for about fifteen years
“the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs.”

(www.solaresearch.org/mission/about)
Goals

• Joint goal of exploring the “big data” now available on learners and learning

• To promote
  – New scientific discoveries & to advance science of learning
  – Better assessment of learners along multiple dimensions
    • Social, cognitive, emotional, meta-cognitive, etc.
  – Better real-time support for learners, leading to genuinely individualized instruction
Many types of EDM/LA Method
(Baker & Siemens, 2014; building off of Baker & Yacef, 2009)

• Prediction
• Structure Discovery
• Relationship mining
• Distillation of data for human judgment/Visualization
• Discovery with models
Prediction

• Develop a model which can infer a single aspect of the data (predicted variable) from some combination of other aspects of the data (predictor variables)

• Which learners are bored?
• Which learners will fail the class?
• Which learners will quit the training program?
• Which learners will fail to demonstrate the skill in real-world tasks?

• Infer something that matters, so we can do something about it
Structure Discovery

• Find structure and patterns in the data that emerge “naturally”

• No specific target or predictor variable

• Are there groups of students who approach the same curriculum differently?

• Which students develop more social relationships in discussion forums?
Relationship Mining

• Discover relationships between variables in a data set with many variables

• Are there more effective trajectories through a curriculum (a set of courses, learning objects, etc.)?

• Which aspects of the design of learning systems have implications for student engagement?
Many applications

• Failure/success prediction
• Automated detection of learning, engagement, emotion, strategy, for better individualization
• Informing instructors, managers, and other stakeholders
• Basic discovery in education
Adaptive Learning requires

1. Determining something about the student
2. Knowing what matters
3. Doing the right thing about it
1. Determining something about the student
2. Knowing what matters
3. Doing the right thing about it
Quite a bit of successful work

- What has been achieved in academic projects
- Still outstrips what is available at scale commercially
Stuff We Can Infer: Learning

• Has the student learned the current skill? (Corbett & Anderson, 1995; Baker, Corbett, & Aleven, 2008; Pavlik, Cen, & Koedinger, 2009; Khajah et al., 2016; Wilson et al., 2016; Ekanadham & Karklin, 2017)

• Where in the learning sequence is the student? (Desmarais & Pu, 2006; Adjei, Botelho, & Heffernan, 2016)

• Is the student wheel-spinning: making no or minimal progress? (Beck & Gong, 2013; Matsuda et al., 2017; Botelho et al., 2019)
Stuff We Can Infer: Complex Learning

• Is the student learning to solve complex problems that require inquiry? (Sao Pedro et al., 2013; Baker & Clarke-Midura, 2013)

• Is the student developing rich conceptual understanding in complex domains such as physics and computational thinking? (Shute & Ventura, 2013; Rowe et al., 2015, 2019)
Stuff We Can Infer: Robust Learning

• Will the student remember what they learned? (Jastrzembski et al., 2006; Pavlik et al., 2008; Wang & Beck, 2012)

• Is the student prepared for future learning? (Baker et al., 2011; Hershkovitz et al., 2013)
Stuff We Can Infer: Meta-Cognition

• How confident is the student? (Litman et al., 2006; McQuiggan, Mott, & Lester, 2008; Arroyo et al., 2009)

• Is the student asking for help when they need it? (Aleven et al., 2004, 2006)

• Is the student persisting in the face of challenge? (Ventura et al., 2012)
Stuff We Can Infer: Disengaged Behaviors

• Gaming the System (Baker et al., 2004, 2008, 2010; Walonoski & Heffernan, 2006; Beal, Qu, & Lee, 2007; Paquette et al., 2019)

• Carelessness (San Pedro et al., 2011; Hershkovitz et al., 2011)
Stuff We Can Infer:  
Affect  
(Emotion in Context)  

- Boredom  
- Frustration  
- Confusion  
- Engaged Concentration/Flow  
- Curiosity  
- Excitement  
- Situational Interest  
- Joy/Delight  

- (D’Mello et al., 2008; Mavrikis, 2008; Arroyo et al., 2009; Conati & Maclaren, 2009; Lee et al., 2011; Sabourin et al., 2011; Baker et al., 2012, 2014; Paquette et al., 2014, 2015; Pardos et al., 2014; Kai et al., 2015; Hutt et al., 2019)
No physical sensors needed

• Now feasible to infer these constructs solely from student interaction with the learning system

• Although using sensors, where feasible, can increase model quality (Kai et al., 2015; Bosch et al., 2015)
How are they developed?

• Obtain some indicator of “ground truth”
  – Existing data on student quitting/failure/performance
  – Tests of robustness of learning/retention
  – Self-reports of emotion or attitude
  – Annotation of log data for strategy or behavior
  – Field observations of engagement, strategy, emotion
    • Less relevant in this particular historical moment
Use data mining to find log data indicators that co-occur with ground truth

• Distill features of interaction hypothesized to correlate to desired construct
  – Best to use theoretical understanding and automated discovery together (Sao Pedro et al., 2012; Paquette et al., 2015)

• Input into standard data mining/machine learning algorithms using Python/R/etc.
Test model generalizability

• In K-12, important to test transfer across rural, urban, and suburban schools, and across ESL learners (Ocumpaugh et al., 2014; Karumbaiah et al., 2018)

• In universities and adult learners, less clear evidence
  – Anecdotal reports that it is problematic to transfer models between very different universities or culturally distinct countries
1. Determining something about the student
2. *Knowing what matters*
3. Doing the right thing about it
Example

• Consider the students taking an advanced MOOC on data science in education
  – A mixture of graduate students, university faculty, school administrators and teachers, IT workers, and data scientists

• Student interaction within the MOOC can predict whether the student will eventually submit a scientific paper in the field (Wang et al., 2017)

• Forum lurkers are more likely to submit a scientific paper than forum posters!
  – Even though forum posters are more likely to complete the course
Another example

• Student knowledge and specific disengaged behaviors in middle school math predicts
  – End-of-year tests (Baker et al., 2004; Pardos et al., 2014; Fancsali, 2015; Kostyuk et al., 2017)
  – College admission (San Pedro et al., 2013)
  – College major (San Pedro et al., 2015)
  – First job after college (Almeda et al., in press)
Examples

• If a student “games the system” in math class when they are 11

• They are less likely to go to college, less likely to major in STEM in college, and less likely to have a STEM job when they are 22 years old
1. Determining something about the student
2. Knowing what matters
3. *Doing the right thing about it*
What do we do?

• When we know that a student is bored... or gaming the system... or has shallow learning... or etc. etc. etc.
Huge Space of Potential Interventions
Huge Space of Potential Interventions

- Automated interventions delivered by animated agents
Goal: Determine how one variable you choose affects the boiling point of ice

EXPERIMENT: Collect data to help you test your hypothesis. ... more

My Hypothesis

If I change the amount of ice so that it decreases, the time the ice takes to melt decreases.

<table>
<thead>
<tr>
<th>Independent Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>amount of heat</td>
</tr>
<tr>
<td>High</td>
</tr>
<tr>
<td>amount of ice</td>
</tr>
<tr>
<td>300 grams</td>
</tr>
<tr>
<td>container cover</td>
</tr>
<tr>
<td>cover</td>
</tr>
<tr>
<td>size of the container</td>
</tr>
<tr>
<td>Small</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Trial Data</th>
<th>Independent Variables</th>
<th>Melting Temp (°C)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trial</td>
<td>Heat Level</td>
<td>Liquid Amount</td>
</tr>
<tr>
<td>Number</td>
<td>Cover Size</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>true</td>
<td>Large</td>
</tr>
<tr>
<td>2</td>
<td>false</td>
<td>Medium</td>
</tr>
<tr>
<td>3</td>
<td>true</td>
<td>Small</td>
</tr>
</tbody>
</table>

I think the data you're collecting won't help you test your hypothesis because you aren't designing a controlled experiment.

Show what I said
Hey, are you just playing with the buttons? Take your learning seriously or I will eat you!!!
Messages to learners

• “Every single man in this Army plays a vital role, said General Patton. Don’t ever let up. Every man has a job to do and he must do it.” (DeFalco et al., 2018)
Huge Space of Potential Interventions

- Stealth interventions that change learner experience in subtle ways
- Mastery learning
- Adjusting difficulty or scaffolding
Huge Space of Potential Interventions

- Reports to instructors, managers, the learners themselves...

<table>
<thead>
<tr>
<th>Module Level</th>
<th>% Mastered</th>
<th>% In Progress</th>
<th>% Not Attempted</th>
<th>% Quit</th>
<th>% Wheel Spinning</th>
<th>Min Time Spent</th>
<th>Mean Time Spent</th>
<th>Max Time Spent</th>
<th>Min Mastery Time</th>
<th>Mean Mastery Time</th>
<th>Max Mastery Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Module - Precision Measurement with Simplify Fractions</td>
<td>60%</td>
<td>10%</td>
<td>0%</td>
<td>0%</td>
<td>30%</td>
<td>0.00 min</td>
<td>64.84 min</td>
<td>96.72 min</td>
<td>35.02 min</td>
<td>42.97 min</td>
<td>61.00 min</td>
</tr>
</tbody>
</table>
Dear [Name],

It is just amazing how fast our first week of Physical Modelling passed by. I just want to check whether I have all your details correct. I have recorded your name as [Name] and your student ID is [ID]. You are exempted from the lab program, your total mark will be 19% out of 25%. Please let me know in case there is anything I didn’t get quite correct.

Please don’t forget that our first homework assignment has been released already. This assignment is due 11.00 pm Friday next week.

I noticed that you haven’t attempted your first week assignment yet. Don’t leave it to the last minute when you might not have access to the internet. As repeat student you are expected to do all WileyPLUS assignments as well as sit for the mid-semester exam.

Kind regards,
End of Week 3 feedback

Dear [Name],

Quite a few students had to move lab classes the past two weeks. This is just to confirm that I have you on record that you are now in lab Group 18 and that your online lab report should be submitted at our Group 18 pages.

You had a good start with Physical Modelling and seem to be well on track. You managed to achieve 9 out of 10 marks in your WileyPLUS assignments. Your lab reports came back with 7 out of 7 marks.

I noticed you are a keen participant of our lecture exercises. Did you know that they can be accessed before as well as after the lecture, not just during lecture? You seem to have had problems with one of the forces questions. Please have a look at HRW Chapter 3.2.2 where this case is discussed in more detail.

Please don’t forget that the our third homework assignment has been released already. This assignment will be due 11.00 pm Friday next week.

Kind regards,
Analyzing what content is working well/poorly

• Using automated models to determine which content is learned slowly, or has unexplained patterns in student errors (Corbett & Anderson, 1995; Agarwal et al., 2018; Baker, Gowda, & Salamin, 2018)

• Example – Baker, Gowda, & Salamin (2018) where able to determine which instructional videos led to improved student performance, and passed this info on to the content team
Analyzing what content is working well/poorly

- Example – TRANSFR provides content authors data on which content is harder and more time-consuming for students
Huge Space of Potential Interventions

• Still an open area for the field

• And an area of considerable ongoing research for my lab
Where is it used?

• K12 – a lot
• Undergraduate – somewhat
• Graduate – rarely
• Professional Learning – rarely

• An opportunity!
A lot of potential
A lot of potential

• But also a lot of snake oil
Some considerations for “getting it right”
In-house or external?
In-house or external?

• If you hire talent for analytics/data mining
  – Try to find at least one team member who has expertise in the type of data you’re working with

• Not all data is the same

• What you do with your models isn’t always the same
In-house or external?

• You wouldn’t hire an education researcher to conduct a medical trial or manage your stock portfolio

• Similarly, don’t just hire people with experience in financial data or bioinformatics to be your educational data mining team
Problem

• Even now, there still aren’t enough people with expertise in educational data to go around

• Hybrid teams seem to work
• Embedding mentor consultants with expertise seems to work

• No-domain-expertise teams don’t function as effectively
In-house or external?

• If you go with an outside team, make sure you know what they’re doing and why

• “Trust me” is simply not good enough
Collect Evidence

• Make sure you collect the evidence to be sure that the approach you’re using is working
  – Do experiments or quasi-experiments
  – Collect data on metrics like
    • Program Completion       Job Performance
    • Course Evaluations       Grades (if relevant)
    • Student Self-Efficacy Surveys
    • Indicators of Participation in online activities
      – Assignments
      – Forums
Another consideration when hiring external teams

• Make sure you’re getting a solution customized to your needs

• Take, for example, the problem of retention analytics

• Some vendors build one model once and then reuse it for every client

• Or build a “model” with no data at all
Example

• College retention analytics
• Some vendors build one model once and then reuse it for every client
• Or build a “model” with no data at all

• Ideally, an organization should be using a model built and validated on data from their organization
• If this isn’t possible in year 1, the model should at minimum be developed and tested on data from multiple organizations similar to theirs
Understanding what the model means
Ideally

• You won’t just get a prediction
Ideally

• You won’t just get a prediction

• *Or* a huge number of indicators
Ideally

• You won’t just get a prediction

• Or a huge number of indicators

• You’ll get information on why that prediction was made
  – Why a specific learner is at-risk
  – Why specific curricular material is less effective
  – Why a collaborative team is less effective
In interpreting this evidence

- Important for the people receiving the data to receive some training in what the indicators mean

- And the context they occur in

- Many indicators are context-specific
Difference by week
(Baker, Lindrum, Lindrum, & Perkowski, 2015)

• Not having opened e-textbook on first day of course
  – Catches most of the students who will fail
  – Also catches many students who won’t fail

• Not having opened e-textbook on day 14 of course
  – Almost always results in failure
  – But does not catch all students who will fail
Look Further
Right now

• Most of the use of learning analytics is focused on immediate retention
  – Will this student pass this course

• Consider longer-term indicators
Fine-grained behavior now can predict big outcomes later

• Participation in MOOC course -> Participation in field

• Engagement in middle school math → College attendance
Go as far as you can in tracking outcomes

- For example, if I was building an analytics model for retention at Penn, I would want to try to predict
Predict

• Who is on track to
Predict

• Who is on track to
  – Graduate from Penn
Predict

• Who is on track to
  – Graduate from Penn
  – Succeed in their career
Predict

• Who is on track to
  – Graduate from Penn
  – Succeed in their career
  – Be a credit to Penn
Predict

• Who is on track to
  – Graduate from Penn
  – Succeed in their career
  – Be a credit to Penn
  – Someday donate lots of money to dear old Penn
Predict

• Who is on track to
  – Graduate from Penn
  – Succeed in their career
  – Be a credit to Penn
  – Someday donate lots of money to dear old Penn

• Sorry, I thought I was meeting with the development office for a minute there
The Big Idea

• Thanks to the big data now becoming available on student learning
The Big Idea

• Thanks to the big data now becoming available on student learning
• And modern data mining methods
The Big Idea

• Thanks to the big data now becoming available on student learning
• And modern data mining methods
• We can make inferences about students in real-time
The Big Idea

• Thanks to the big data now becoming available on student learning
• And modern data mining methods
• We can make inferences about students in real-time
• That are predictive of long-term outcomes
Eventual Goal

• Track a student’s engagement/knowledge/etc. now
Eventual Goal

- Track a student’s engagement/knowledge/etc. now
- Predict the longer-term impact
Eventual Goal

• Track a student’s engagement/knowledge/etc. now
• Predict the longer-term impact
• Intervene to help re-engage students and support their learning
Eventual Goal

• Track a student’s engagement/knowledge/etc. now
• Predict the longer-term impact
• Intervene to help re-engage students and support their learning

• Helping e-learning to achieve its goals of individualizing to help learners develop skills and achieve their professional goals
Lots of Challenges
Lots of Challenges

• But lots of opportunities as well
Learn More

“Big Data and Education” MOOC, running on edX now
All lab publications available online – Google “Ryan Baker”