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Alternatively, the teacher can wait until she or he has better information about the exact struggles of each student. But in a traditional classroom, that might be fairly late in the learning process to return to the topic (for instance, not until after homework has been completed or even at the point of the exam). The teacher can certainly write feedback to the student on their exam or homework assignment when grading it. But will the student remember what they were thinking several days earlier? Will the student even read the feedback?

Contrast this situation with one in which the student is learning with a software package like *ALEKS* (Canfield, 2001) or Redbird (Suppes & Zanotti, 1996) that provides teachers with reports on student performance. First of all, *ALEKS* and Redbird (and most online learning systems nowadays) provide students with immediate feedback that, where appropriate, explains to students why their answers were wrong. Students can even obtain a worked example explaining how to solve the problem. Equally important, the system can informr ca90 BDC BT/T1D 1 (rading i)-kwCoir ansœrrfeear

Disengagement matters for learning: If a student is not turning in their work on time, is not participating in class activities or is simply procrastinating and starting late, they are at considerable risk for performing poorly. Through technology, it is now feasible to automatically identify many forms of disengagement. Systems now in use by hundreds of universities and colleges identify which students are becoming disengaged, and present this information to instructors along with suggestions for how to support their students in re-engaging.

This type of approach has been shown in several studies (including a landmark study in 2014 by Milliron, Malcolm, and Kil) to improve the likelihood that students will pass classes and stay in college. The technology needed to implement this type of approach in K–12 already exists, but most schools that use it primarily focus on indicators such as disciplinary incidents like fighting or skipping class, a fairly late stage in the process of disengagement. Still, there is potential for leveraging the rich data available on K–12 students to help re-engage them as well. I personally expect to see these technologies developed and adopted within K–12 to a much greater degree within the next few years.

Why Data-Driven Approaches Work

Some potential questions about the use of online learning technologies include:

How do we know the data is accurate?

How does a computer know that a specific student is making progress?

How can a computer tell when a student is struggling or with what?

Should we trust a report coming from a computer?

It's important to remember that we never know for certain what is going on in a student's mind. Any mistake could stem from multiple causes, including not knowing how to solve the problem, having a misconception, or even carelessness on the part of the student.

For a classroom teacher working on his or her own without the support of an online platform, it's difficult to gain insightful information about what each student knows. A student might answer a question in class, but is that enough information to really know what's going on in the student's head?

Even in instances when there is clear information (for instance, immediately after a student turns in his or her homework), a teacher may not have enough time to study each student's pattern of responses to understand the implications. By comparison, a computer can look at all of the student's answers over time. As the student responds to questions, the system compiles the evidence into a profile of what the student knows.

School teachers can't be expected to determine whether a computer program like Bayesian Knowledge Tracing is better than, for example, a Recurrent Neural Network. Fortunately, they don't have to. There is now a very active area of scientific research, which compares computer programs that attempt to determine what the student knows or doesn't know. Researchers at dozens of universities and education companies are publicly debating which approaches are best.

While debate continues in journals and at scientific conferences, several studies (most recently an award-winning scientific paper by Khajah, Lindsey, and Mozer at the University of Colorado) have repeatedly reached an interesting conclusion: The difference between the best and most recent computer models and those from twenty years ago is surprisingly small—around 10%. With a small number of exceptions, whichever online learning software you are using to measure what students know, as long as it is measuring their correctness while learning (instead of just testing them and not helping them learn), it is probably good enough to be useful to you.

This is true because ***the real power of data lies in having a lot of it.*** A student using an online learning platform like *ALEKS* or Redbird could enter between 30 and 100 answers an hour. That's a ton of information. In that hour, a student may complete 10 2s a ton osirrssiat g4 (w)-5 1, 8ound 10%. d0ompme2

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