Estimation of Learning Progress

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Monitoring the progress of student learning is an important part of teachers' data-based decision making. One such tool that can equip teachers with information about students' learning progress throughout the school year and thus facilitate monitoring and instructional decision making is learning progress assessment. In practical contexts and research, estimating learning progress has relied on approaches that seek to estimate progress either for each student separately or within overarching model frameworks, such as latent growth modeling.

progress monitoring

Bayesian analysis

robust estimation

1. Introduction

The term progress monitoring refers to systematically gathering information on students' learning progress to guide feedback and instructional decision making. A prominent example of progress monitoring is curriculum-based measurement (CBM; Deno 1985), occurring in the context of special education. In CBM, parallel weekly assessments of core competencies such as reading are used to assess students' responsiveness to teachers' instructional decisions. An important feature of CBM is that assessments are indicators of and interpreted in relation to a desired learning goal (Fuchs 2004). Another similar form of progress monitoring is learning progress assessment (LPA), which refers to progress monitoring in everyday classrooms. LPA as implemented by the assessment system quop (Souvignier et al. 2021), for example, has longer time intervals between successive measurement points as compared to CBM. In addition, LPA tries to balance differentiated assessment of relevant skills (i.e., math and reading achievement) to allow differentiated feedback and acceptable psychometric properties. For example, the guop-L2 test series for reading assessment in second grade includes three subscales at all levels of language (i.e., the word, sentence, and text levels; Förster et al. 2021; Förster and Kuhn 2021). If a student performs well at the word level but poorly at the sentence and text levels, the fit of instruction would be high if the teacher supports the student's sentence reading before supporting more complex higher-order reading comprehension strategies. The success of such progress monitoring implementations (regardless of whether CBM or LPA) can be evaluated via estimates of learning progress (Fuchs 2004).

2. Estimation of Learning Progress

The idea of estimating learning progress using the slope of a student's data plotted in a bivariate scatterplot can be traced back to work prior to the emergence of CBM (<u>Deno and Mirkin 1977</u>). Conceptually, the linear slope that occurs when plotting student performance against measurement time points allows one to assess the student's average learning progress over time (<u>Silberglitt and Hintze 2007</u>). While numerous methods exist for estimating

slopes (Ardoin et al. 2013), in the context of progress monitoring, researchers have most often used ordinary least squares estimation. Historically, ordinary least squares can be understood as having replaced other methods such as quarter-intersect or split-middle (both methods require splitting the data into two halves to identify the median of each halve which builds the basis for drawing the slope; split-middle further requires that the same number of points is situated below and above the line) as the default in progress monitoring. Ouarter-intersect or split-middle were considered more applicable in early years of CBM practice when computational power was not regularly available in school settings and growth estimates had to be calculated and drawn by hand (Ardoin et al. 2013). In addition, it was demonstrated in simulation studies that ordinary least squares estimates outperform estimates based on the medians of splitted data (Christ et al. 2012). Most recently, researchers have discussed and examined approaches that can be understood as either robust methods (e.g., non-parametric Theil-Sen regression; Bulut and Cormier 2018; Vannest et al. 2012) or Bayesian methods (Christ and Desjardins 2018; Solomon and Forsberg 2017). The ordinary least squares estimator makes assumptions (e.g., homoscedastic normally distributed errors) that can be violated in empirical data, and it is prone to influencing outliers. Indeed, the non-parametric Theil-Sen estimator does not require such strong assumptions and is robust with respect to outliers. Advantages of Bayesian estimation methods have been nicely summarized by Solomon and Forsberg (2017, p. 542): it can be robust, prior information can be utilized, and it has a natural compatibility with data-based decision making (i.e., posterior probabilities inform about intervention success).

Importantly, students may occasionally be tired or unmotivated when taking a test. In addition, researchers have identified that particular factors related to data collection (e.g., the place where the assessment is conducted, the person administering and/or scoring the test) may cause scores to fluctuate (Van Norman and Parker 2018). Hence, in the context of progress monitoring (i.e., repeated assessment of learning progress to inform feedback and instructional decision making), such fluctuations potentially influence performance at single measurement points and might yield single observations that strongly deviate from what might be expected (Bulut and Cormier 2018). Consequently, such outliers can influence estimates of student learning, especially when they occur at the beginning or toward the end of the period of assessment (Bulut and Cormier 2018). However, an accurate evaluation of student learning is critically important in the context of progress monitoring because such a databased approach to decision making (Espin et al. 2017) relies on dynamic loops of assessment, instructional decisions, and feedback. To avoid this problem, Christ and Desjardins (2018) suggested using Bayesian slope estimation, which was found to be more precise and more realistic compared to ordinary least squares regression (Christ and Desjardins 2018).

3. Factors That Influence the Quality of Learning Progress Estimates

The quality of slope estimates in the context of progress monitoring does not only depend on the method of slope estimation. Both empirical and simulation studies have identified several other factors affecting the psychometric integrity of slope estimates such as measurement invariance, procedures of data collection, data collection

schedules, and the number of measurement points. These factors from the perspective of CBM can see <u>Ardoin et</u> <u>al.</u> (2013).

Measurement invariance of the tests used is important to allow a straightforward interpretation of learning progress. While Ardoin et al. (2013) concluded that empirical tests of probe equivalence in CBMs are scarce in the literature, the importance of equivalent (i.e., parallel) tests has been emphasized in progress monitoring research. As recommended by <u>Schurig et al.</u> (2021, p. 2): "... a good progress monitoring test should first check the dimensions, then the invariance...". The available evidence of CBM probes in terms of equivalence suggests that probes may not display form equivalence (Cummings et al. 2013) and findings indicated that psychometric quality of slope estimates depends on the chosen probe sets (Christ and Ardoin 2009). However, the guop-L2 test that was used in this work has demonstrated its factorial validity (Förster et al. 2021) and strong evidence in terms of practical equivalence based on a thorough item-response theory investigation focusing on accuracy and speed (Förster and Kuhn 2021), as well as strict measurement invariance when items are scored for efficiency of reading (Förster et al. 2021). The relevance of procedures of data collection has been already discussed in the introduction above. Clearly, variations in administration procedures can cause fluctuations in test performance, starting with varying times on the testing day at which tests are administered to a simple change of the testing room, for example. Beyond such potential influences on test performance, Bulut and Cormier (2018) thoroughly discussed progress monitoring schedules and the overall number of assessment points. They highlight that optimal schedules depend on the expected rate of improvement, which in turn can depends on various student characteristics. For example, from the perspective of CBM, a comprehensive simulation study revealed that validity and reliability of slope estimates depend on the overall duration (i.e., in weeks) of progress monitoring as well as the number of assessments within each week (Christ et al. 2013). Christ et al. (2013) found that valid and reliable slope estimation required at least four weeks of progress monitoring. While the overall duration of progress monitoring in LPA tends to be longer (e.g., 31 weeks), the overall schedule must be considered to be clearly less dense with successive measurement timepoints being separated by approximately three-week intervals (Souvignier et al. 2021), for example. Beyond these aspects of the progress monitoring schedule, increasing the number of measurement points will increase the measurement precision of slope estimates. However, adding measurement timepoints close in time will, for most core skills, not result in huge information gains when it comes to slope assessment.

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