any other analysis methods that are currently in LearnSphere (e.g., Bayesian Knowledge Tracing [1], Performance Factors Analysis [6], MOOC activity analysis [3], and others) or that have been uploaded to LearnSphere as a custom workflow, and (3) sharing their own analysis workflows with the community of researchers. Without any prior programming experience, researchers can use LearnSphere's drag-and-drop interface to compare, across alternative analysis methods and across many different datasets, model fit metrics like AIC, BIC, and cross validation as well as parameter estimates themselves.

Workshop submissions will involve a brief description of an analysis pipeline relevant to modeling educational data as well as accompanying code. Prior to the workshop itself, the organizers will coordinate with authors of accepted submissions to integrate their code into Tigris. A significant portion of the workshop will be dedicated to hands-on exploration of custom workflows and workflow modules within Tigris. Authors of accepted submissions will present their analysis pipelines, and everyone attending the workshop will be able to access those analysis pipelines within Tigris to a variety of freely available educational datasets available from LearnSphere. The end goal is to generate, for each workflow component contribution in the workshop, a publishable workshop paper that describes the outcomes of openly sharing the analysis with the research community.

Finally, workshop attendees will discuss bottlenecks that remain toward our goal of an easier, more open way to share analytic tools. We will also brainstorm possible solutions. Our goal is to create the building blocks to allow groups of researchers to integrate their data with other researchers we can advance the learning sciences as harnessing and sharing big data and analytics has done for other fields.

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Keyword Index

academic achievement	312
academic dishonesty	262
active learning	414
actor-based model	336
adaptive assessment	466
adaptive learning	448, 466
adaptive tutoring system	460
additive factor model	135, 376
ADL	416
adult literacy	128,376,396
affect	382
agglomerative clustering	256
AI Technologies	1
ALEKS	312
ANOVA	202
argument diagrams	296, 439
assessment	466
ASSISTments	390
association rule mining	318
at-risk students	384
attention aware interfaces	88
attention-aware	8
attention-aware learning	226
augmented graph grammars	296
authenticity	162
automated assessment	214
automated bug discovery	414
automated grading system	439
automatic composition of test paper	352
automatic discovery	7
automatic feedback	439
automatic grading	350
AutoTutor	376
banner	346
bayesian knowledge tracing	3, 143, 186, 448
bayesian network	398
behavioral data	64
best educational practices	374
BKTSR	186
blended courses	378
blog	362
business education	366