Methodologies and technologies of the Grockit learning platform

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algorithms+analysis+assessment

Grockit provides a place for students to master new concepts and exercise what they learn through a set of study modes designed to accommodate a variety of learning styles and learner preferences. These include: (1.) *small group study*, which leverages the power of collaborative learning dynamics to provide students with a social learning network that can help motivate and assist them, (2.) *individual study*, which builds and uses a data-driven model of a student's abilities to provide that student with appropriate challenges for learning, (3.) *instructor-led classes*, which draw on a teacher's domain knowledge and experience to provide a guided and structured path for groups of learners. The algorithms and affordances used in these three study contexts draw on three corresponding fields of research:

Collaborative peer-driven study in social learning networks

Research in *Computer Supported Collaborative Learning* (Stahl et al., 2006) informs the "group study" activities in Grockit. The design of the platform has focused on identifying how to best facilitate and support productive collaborations among peer learners in real-time.

Group study in Grockit re-introduces several valuable aspects of the classroom largely missing from asynchronous web-based learning environments: (1.) the interaction and camaraderie within a cohort of peers, (2.) the opportunity to get immediate answers to pressing questions, and (3.) the motivating force to keep the student engaged over time in the learning activity (Bader-Natal, 2009). By re-introducing peer cohorts and live question-answering to the learning experience, Grockit supplements the domain-specific intelligence of the system itself with the natural intelligence of other learners studying that topic. In group study sessions, students alternate between solving problems on their own and discussing these solutions with others in small groups. Experiments examining similar alternating models have demonstrated significant learning gains resulting from the peer discussions, with the learning transferred to new problems and persisted over time (Smith et al., 2009). Notably, learning gains were observed even when none of the students in the group correctly answered the question initially. This is consistent with Vygotsky's "Zone of Proximal Development", in which an expert or more advanced peer can enable a student to grasp a concept that would otherwise be beyond his grasp when studying alone (1978). Grockit's group study leverages a similar alternating-mode model to provide students with the opportunity to solve a problem alone, then discuss the problem once all students in the group have responded and have seen the accuracy of their response.

Grockit complements these synchronous learner interactions with two types of asynchronous interactions: one type around the domain knowledge and the other around the social learning experience itself. For the former, each question that appears in a Grockit study session has an asynchronous discussion thread associated with it, in which students can ask and answer questions in more detail than is possible in the faster-paced synchronous sessions. For the latter, Grockit has adapted a number of features native to social networking applications for its network of learners. Each student has a learner profile page that includes their learning goals, study plans, past achievements, recent study partners, friends, and endorsements from students and tutors with whom they have studied in the past. Some of these are student-authored and some are automatically generated by the system, and the common goal is to meaningfully situate students within the network of their fellow learners.

One noteworthy property of Grockit's small study group model is that the learning context improves as the community of learners scales. While increasing the number of *students* in a study group quickly changes the interactions that occur within it, scaling the number of *groups* increases opportunities for adaptive meta-level system design. Without changing the dynamics of the interaction, Grockit can place students in groups more intelligently, and can support synchronous group study sessions on increasingly specific study topics.

Computer-adaptive individual study

Research in *Intelligent Tutoring Systems* (Aleven et al., 2008) and *Artificial Intelligence in Education* (Dimitrova et al., 2009) informs the design of the "solo practice" activities in Grockit, toward providing each learner with a customized experience designed to simultaneously challenge and support that that learner.

The basis of the student model constructed for solo study in Grockit is *Item Response Theory* (Lord, 1980), which was developed by the statistics community as a basis for educational assessment and measurement. Grockit has drawn on a variety of such models, including the one-parameter Rasch Model (Rasch, 1980) and Birnbaum's three-parameter model (de Ayala, 2008). These models enable Grockit to take advantage of the tens of thousands of new student responses to questions recorded every day to automatically refine Grockit's estimates of student abilities, question difficulties, and their intersection: probabilities of response accuracy. Grockit uses these predicted probabilities to guide the question selection algorithm in individualized study sessions. The system is tuned to present questions for which the student have a near-50% likelihood of providing an accurate response, focusing study on questions that are neither too difficult to learn nor too easy to benefit from. This statistical model serves as the basis for Grockit's definition of challenge appropriateness. This problem selection algorithm offers a secondary benefit: It constructs a learning environment conducive to "flow", Csíkszentmihályi's notion of a hyper-focused, high-productivity state created when the difficulty of the challenge matches the ability level of the individual (1990).

Expert-led online courses

The technologies and affordances that Grockit provides in "instructor-led lessons" are informed by work in the *E-Learning* (Bastiaens, 2009) community, primarily how teachers may use available online tools to make their teaching more effective. Grockit provides instructors with a collection of collaboration tools to draw on during instruction to help make their online teaching sessions more actively involve student participation. Shared whiteboards, collaborative document editing, video streaming, and audio conferencing facilities are all currently available for use in expert-led courses.

Grockit offers students a variety of ways to work with instructors. At one end of this spectrum, a student can opt for one-to-one personalized tutoring, a technique proven to be two standard deviations more effective than traditional group instruction (Bloom, 1984). At the other end of the spectrum, a student can enroll in massive open online courses, in which live streaming video lessons taught by the instructor are broadcast online, free of cost and open to anyone. The first such course was offered in 2010, with thousands of enrolled students and hundreds of active participants. Between class sessions, homework was done in Grockit study groups. In doing so, this format pairs the scalability of the video broadcast with the engagement and effectiveness of peer study.

Adaptive assessment

Assessment is most accurate and efficient when the testing environment is highly controlled. In Grockit, this takes the form of a single-student single-sitting *Computer Adaptive Test* (CAT), in which the sequence of questions presented to a student during the test is based on that student's performance on the previous questions in that test (de Ayala, 2008). The question selection algorithm for Grockit CATs is similar to that of the computer-adaptive GRE and GMAT tests: a student's ability is re-estimated after each question using an Item Response Theory (IRT) model, and this estimate is used as a basis for recalculating the Fisher Information Gain of each available item for that student. The item that maximizes information gain based on the current estimate is then determined and presented to the student. Also incorporated in Grockit's CAT item selection algorithm are components designed to provide exposure control and content balancing (Rudner, 2010), two practical issues in the design of high-stakes Computer Adaptive Tests.

In learning domains for which a good external metric is available (such as with students studying for a standardized test), Grockit's internal measurement is calibrated with that external instrument in order to provide a score estimate (and a one standard error confidence interval) for the student on the external metric. The accuracy and precision of these estimates improve with the quantity of available data, so score projection accuracy improves automatically as new data is continuously incorporated into the estimation of the Grockit's underlying IRT models.

In addition to these formal assessment techniques, Grockit offers another powerful approach to measuring student performance: *embedded assessment* (Shute et al., 2009). Every time a student answers a question in Grockit, whether in individual practice, group study, or a lesson, the student's response is recorded and the system's model of the student is re-estimated. Grockit maintains a constantly-updated running estimate of each student's performance based on this embedded assessment, which can be used to track progress and provide the student and teacher with skill-grained feedback.

Game dynamics in learning

Grockit incorporates a set of game dynamics commonly found in casual games: points, badges, leader-boards, challenges, and duels. These serve to make the activity more engaging by incorporating collections, competitions, and reputation into the experience. Two distinct point systems are in place, one to motivate participation and performance (earned based on response accuracy and question difficulty) and the other to motivate helpfulness and collaboration (earned by participating in group discussions in ways that others find beneficial). The second system helps to set the tone of the learning environment, and provides a means for earning a reputation through marks of peer-recognition. Leader-boards for high earners of this currency provide additional profile visibility and social standing, and act as an incentive for other students to become more active and helpful members of the community. One of the most frequent words used by students piloting Grockit as part of an Algebra course in 2010 was "fun," primarily a result of the game dynamics incorporated into the activity.

Learning analytics and educational data mining

Grockit's web-based learning system offers the ability to collect and analyze fine-grained educational data on the performance and activity of students, a useful basis for better understanding and supporting learning among those students. To take full advantage of the rich data available, Grockit has developed an internal pipeline for processing and presenting advanced learner analytics (Bader-Natal and Lotze, 2011) and educational data mining (Romero et al., 2010). The availability of this pipeline enables stakeholders to pose a variety of interesting questions, often focused on specific subsets of students. As Grockit's analytics system has matured, the number of stakeholders, the number of interesting questions, and the number of relevant sub-populations of students has also grown, making for an increasingly powerful data analysis environment, designed to make this type of analysis possible, flexible, and scalable.

Beyond research use by learning system designers within Grockit, the analytic capabilities of the system are increasingly designed to be shared directly by the students and teachers that study on Grockit on a daily basis. Each question in Grockit has a growing assortment of metadata associated with it – such as the concepts or skills required to solve the problem – and this metadata provides a way to organize collected responses when evaluating a student's knowledge. Skill-by-skill performance analysis provides learners with useful feedback to inform self-directed study, and provides instructors with aggregate feedback on which concepts a group of students mastered and those that would require additional instruction time to master.

Conclusion

Grockit is structured as a set of learning opportunities and tools from which a student can pick and choose, which allows for flexibility and variation in learning paths. In each mode of study – individual practice, peer group study, and instructor-led lessons – two different combinations of control and constraint are supported: student-controlled study experiences and system-controlled study experiences (Dron, 2007). For the former, Grockit equips learners with data to inform their decision about their study time allocation, such as the interactive performance analytics. For the latter, Grockit constructs an experience based on an automated analysis of the data, such as the individual study sessions composed of questions selected based on a students prior history and current estimate of ability. This flexibility gives self-directed learners control over the amount of control that they wish to exert on their experience, and it gives educators and institutional adopters the ability to specify the subset of these modes that they find most appropriate for their learners.

Educational researchers know that students can learn more than they do today in a traditional classroom, as researchers have seen it, measured it, and replicated it. But while an expert tutor can help a student perform up to two standard deviations above traditional classroom levels, one-to-one personalized tutoring is too expensive to be the solution on a large scale (Bloom, 1984). There are a number of promising alternatives to expert tutoring, and Grockit has been developing several of these: a mastery-oriented adaptive system for individualized learning, a culture and toolset built around peer-assisted learning, and a hybrid instructor–peer model for highly-scalable expert-led courses. The methodologies and technologies built into Grockit's platform were designed to meet this challenge in order to create a learning environment that is highly engaging, scalable, and effective.

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