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System Design and Architecture of an Online, Adaptive, and Personalized Learning Platform

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A Summary Report for: *“Towards Intelligent Societies: What Motivates Students to Study Science and Math? How Can We Provide Flexible Learning Pathways?”* Sponsored by Fujitsu Laboratories of America

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*“Towards Intelligent Societies: What Motivates Students to Study Science
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by

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Abstract

The authors propose that personalized learning can be brought to traditional and non-traditional learners through a new type of asynchronous learning platform called Guided Learning Pathways (GLP). The GLP platform allows learners to intelligently traverse a vast field of learning resources, emphasizing content only of direct relevance to the learner and presenting it in a way that matches the learner's pedagogical preference and contextual interests. GLP allows learners to advance towards individual learning goals at their own pace, with learning materials catered to each learner's interests and motivations. Learning communities would support learners moving through similar topics. This report describes the software system design and architecture required to support Guided Learning Pathways. The authors provide detailed information on eight software applications within GLP, including specific learning benefits and features of each. These applications include content maps, learning nuggets, and nugget recommendation algorithms. A learner scenario helps readers visualize the functionality of the platform. To describe the platform's software architecture, the authors provide conceptual data models, process flow models, and service group definitions. This report also provides a discussion on the potential social impact of GLP in two areas: higher education institutions and the broader economy.

1. Introduction

Motivation

Education is experiencing many shifts; Clayton Christensen says that it is being “disrupted” by the potential of online learning (Christensen, Johnson, & Horn, 2008). Picciano et al. (Picciano, Seaman, & Allen, 2010) note some barriers to true transformation of education, such as changes in education policy, blended learning adoption, and higher education institutions not embracing online learning. Since they published their analysis in 2010, however, many of these barriers have lowered or even disappeared. The Khan Academy¹ (Khan Academy, n.d.) has enabled widespread blended learning in K-12, and prestigious universities like Stanford, Harvard, and MIT have adopted online education through MOOCs (Massive Open Online Courses).

However, these popular MOOCs utilize an industrial model of education with a “pre-defined course,” where tens of thousands of students must try to learn the same topics at the same pace during a given time period. Students study each topic asynchronously and at their own pace, but the class progresses even if they have not mastered the topics. This emphasis on seat-time instead of topic-based mastery learning causes many students to drop out of the courses—they may have the ability to learn the material, but struggle with the time constraints (Belanger, 2012). Others may not have the educational background or regular access to technology to succeed in current MOOC courses (Ripley, 2012). Given the current state of technology, “courseless,” asynchronous learning could support each learner in mastering the topics she needs, rather than keeping an unnecessary pace.

The goal of using technology to achieve personalized learning stems from the work done by Bloom in 1984 and his “Two Sigma Problem,” which showed that one-to-one tutoring coupled with mastery learning improved student performance two standard deviations above that of a traditional classroom (Bloom, 1984). More recent research in traditional classrooms has also shown the benefits of students learning at their own pace and focusing on topics that interest them (Rose & Meyer, 2002; Tullis & Benjamin, 2011).

In pursuit of achieving one-to-one tutoring via technology, many researchers have investigated recommendation algorithms for matching learners with digital learning materials suited for their personal needs (Hummel, et al., 2007; Tang & McCalla, 2005; García, Romero, Ventura, & de Castro, 2009; Farzan & Brusilovsky, 2006; Recker, Walker, & Lawless, 2003; Romero, Ventura, Delgado, & De Bra, 2007; Tsai, Chiu, Lee, & Wang, 2006). Their research studies have shown promising results for both recommending courses as well as for individual learning materials. Techniques like collaborative filtering, content-based filtering, and hybrid systems have been evaluated.

Some researchers and companies are creating entire classroom experiences centered around such recommendation algorithms (Dede & Richards, 2012; Knewton, n.d.; Siemens, et al., 2011; Time To Know, n.d.; Vander Ark, 2012). Siemens, et al., propose perhaps the most comprehensive such platform, which they call Open Learning Analytics (OLA) (Siemens, et al., 2011). OLA uses analytics to improve individualized content delivery and focuses on organizational and institutional use, with learners participating in traditional “classes.”

¹ Khan Academy, Inc., <http://www.khanacademy.org>

Instead of focusing on teachers and institutions, others have focused on student-centric platforms. The European community has developed a large-scale solution for personalized learning, called ROLE (Responsive Open Learning Environments), which caters to non-traditional learners (ROLE Consortium, n.d.). Currently being tested in five different testbeds, ROLE focuses on a completely learner-driven environment, with minimal guidance and direction from educators or experts. In the ROLE scheme, educators create widgets that teach specific concepts, rather than directing learners towards certain topics. In turn, learners pick their own widgets to “mash up” into individualized learning experiences.

Our platform, Guided Learning Pathways (GLP), falls in between ROLE and Open Learning Analytics when looking at educator and learner roles—it provides a learner-centered environment (inside and outside of the classroom), but with guidance from educators and domain experts. Like these other platforms, GLP would require significant up front investment to create adequate content and a base platform, though the added cost for each additional learner would be minimal. This type of investment would be suitable for large, introductory university courses such as Calculus I, where hundreds of thousands of students with very diverse interests enroll every year—over two hundred thousand enrolled in Calculus I courses in the United States alone, in 2005 (Lutzer, Rodi, Kirkman, & Maxwell, 2005). While the original vision for GLP was outlined in 2002, new technologies and software platforms have since emerged that would lower total investment cost while also improving GLP functionality (Larson, 2002).

To achieve the vision for GLP, an appropriate software architecture needs to be defined. Software architecture has many definitions (Microsoft, n.d.). Essentially, it is the overarching structure of a software platform that takes into account business and future non-technical needs. This includes considering user scenarios, potential changes, and “-ilities” like reliability and scalability. “Good architecture reduces the business risks associated with building a technical solution. A good design is sufficiently flexible to be able to handle the natural drift that will occur over time in hardware and software technology, as well as in user scenarios and requirements.” (Microsoft, n.d.). A software architecture thus presents a framework for a team of developers to work within, but does not dictate technical design details like language or pieces of code.

Research Questions

What would education using a personalized platform like GLP look like?

What kind of software architecture could support a platform like GLP?

What are the potential social implications of an engaging and personalized online learning platform?

Report Outline

This report is the cumulative effort of a three-year collaboration between the MIT Education-as-a-Complex System and Fujitsu Laboratories of America. Throughout this time, MIT researchers have developed prototypes of various components of the system to showcase potential functionality. Much of this early work was done by Naveen Chandra, Hamid Salim and Kittipong Techapanichgul. Research then proceeded to developing a system architecture of the Guided Learning Pathways System, principally done by Cole Shaw. This report is primarily adapted from Mr. Shaw's thesis.

Section 2 presents a future-oriented vision of Guided Learning Pathways. In addition to a discussion on GLP learners, this vision is communicated through descriptions of eight software applications, a detailed learner scenario, and the benefits and features of each app. A learner scenario continues through each app description and provides details on how apps interact with a learner.

Section 3 describes in more technical detail the core architectural components of GLP that are needed to support the vision in Section 2. A two-layer architecture is presented that allows for easy upgradeability, maintainability, and application flexibility. Three types of models are defined to support this two-layer architecture: conceptual data models, process flow models, and service descriptions. Examples of each are given.

Section 4 discusses the social impacts of GLP, in qualitative terms. These impacts are examined at higher education institutions and in the general economy. Within higher education institutions, we examine issues like cost, accessibility, and STEM diversion (with an additional focus on underrepresented minorities). Regarding the general economy, we look at the potential impacts on lifelong learning, jobs, and overall international impacts.

Section 5 provides overall conclusions about the system architecture and social impact analysis for a personalized learning platform called Guided Learning Pathways (GLP).

Appendix A acts as a reference and guide for developers or practitioners. It contains pseudocode and encoding tables that may be useful in designing the data repository and implementing some of the services.

Here at MIT, there are currently exciting developments in online education underway. EdX, a collaboration with numerous other universities, is one of a few MOOCs (Massive Online Open Courses) that have the potential to disrupt and revolutionize education. Many of the ideas developed throughout the Guided Learning Pathways have gained traction among researchers working on edX, leading to Cole Shaw now being employed with MIT's Office of Educational Innovation and Technology. We are excited to see where Guided Learning Pathways will go in the future.

2. GLP Vision

Introduction

This section presents a system-level vision of the Guided Learning Pathways platform. It includes an overview section that describes overarching goals and features. We then describe the learners that GLP will serve. After describing the most important users, we provide eight sections that discuss software applications that enable specific GLP features. These sections include: 1) user visualization, 2) content map, 3) content recommendation algorithm, 4) learning nuggets, 5) nugget recommendation algorithms, 6) intelligent tutors, 7) learning communities, and 8) nugget rating algorithms. Each section contains a basic description of the application, a user scenario as an example, and a discussion on benefits and functionality of the application. Other applications could also integrate into GLP, such as a badging and reward system, though they are not discussed in this paper. This section presents a fluid and evolving description of GLP, and the examples described within represent possible GLP implementations—readers should not interpret them as being the only implementations.

Overview of GLP

Goal of GLP

GLP enables traditional and non-traditional learners to learn what they are interested in, with material best suited for them, while providing a collaborative, dynamic, and engaging online environment. This is a radically improved approach to education compared to the current, “industrial” model. GLP’s use of content maps and focus on topic-based mastery remove many of the challenges of a traditional “course.” Learners in GLP do not need to keep up with other learners, and they do not need to move ahead before mastering the material. Furthermore, learners study topics that help them achieve their individual learning goals, and they are recommended learning materials that engage them—these learning nuggets are tailored to learners’ individual interests, knowledge levels, and learning styles. Social networks, learning communities, and software tutors allow GLP to keep many of the strengths of traditional classrooms.

Essential GLP Terminology

In order to help the reader better understand the discussion of GLP, we introduce some commonly used terminology in Table 1. More detailed explanations of each item will be given in later sections.

Term	Definition
Content Topic	A content topic is an atomistic concept within a domain. Today, all domains (such as calculus) are divided into classes that are taught over a semester or quarter. GLP eliminates the idea of a time-constrained “class” and instead divides domains into topics—arranged into a content map as they are conceptually related to each other. These maps look like directed, acyclic graphs, such as the Khan Academy Knowledge Map for math topics (Khan Academy, n.d.). Content topics that are not directly related to each other can thus be learned in any order. Other topics require pre-requisite knowledge and must be learned sequentially.
Learning Nugget	Learning nuggets are the materials used to learn content topics. They are divided into categories such as case studies, lecture notes, videos, interactive applets, or homework. Each embodies a certain learning style, such as visual, textual, or auditory. GLP could discover these on the Internet (i.e. OpenCourseWare), access them through data repositories, or accept direct uploads from content creators. Regardless of source, all nuggets are screened for quality purposes. This screening addresses concerns that previous initiatives have found with Open Educational Resources (OERs) (EdReNe, 2011).
Pathway	Pathways are groups of content topics that lead towards a learning goal. They include the pre-requisite topics that need to be mastered. Pathways are flexible and can change according to the learner’s interests. Educators can also customize pathways for classes—for example, a biology teacher in Maine may wish to address certain topics that a biology teacher in Arizona may not.

Table 1. GLP Terms and Definitions

System-level Features

GLP has several features that occur at a system level and apply to all of the software applications. Three of these system features are: 1) application modularity, 2) data analytics, and 3) complete personalization.

Application modularity allows GLP to be easily upgradeable in the future. This modularity is enabled by GLP's service-oriented architecture. Modularity means that two different developers could make two distinct "content map" applications and plug them both into GLP, as long as they use the standard content map interface. Afterwards, any learner could decide to use either content map. Thus, all of the applications described in this paper should be thought of as application "categories," where different implementations could replace others in the same app category.

Data analytics will be embedded throughout GLP and allow the platform to improve and personalize each learner's experience. GLP will track learner data and actions from every application, including things like which nuggets they used, which problems they attempted, and who they collaborated with. The data would be made available to applications like the nugget recommendation algorithms, which could then analyze the data in various ways. Combined with application modularity, the data analytics give GLP learners incredible flexibility in using the tools that they prefer. For example, MIT and Stanford could both create nugget recommendation algorithms that use different learner data as inputs. MIT's algorithm might look at the other nuggets the learner has used, while the Stanford nugget algorithm might be more social and use the learner's forum posts and what her friends studied. Some learners may find that they prefer the MIT algorithm, while others may prefer the Stanford one. Since GLP is modular, each learner could choose to use the recommendation algorithm they prefer, with no impact on other learners.

The previous example demonstrated how GLP allows for complete personalization, even down to the version of application each learner uses. The personalization also includes details like the visualization of their pathways, the types of nuggets recommended, and the topics studied. Some of this will be based on learners' expressed preferences, such as the form of visualization. Other personalization details might be determined from a combination of learners' expressed preferences, personal interests, and other learners' actions. Learning style is an example of an expressed preference that could be considered in combination with other factors. Even though it has not been shown that individuals learn best with a single learning style (Pashler, McDaniel, Rohrer, & Bjork, 2008), GLP could use learning style to encourage differentiated instruction.

Learners

Description

Traditional and non-traditional learners are the main users that GLP will serve. Traditional learners are those in age-appropriate learning environments with access to a qualified teacher, while non-traditional learners may include youth in rural areas, people in developing countries, or lifelong learners with specific learning needs. GLP will personalize each learner's experience based on her needs and goals.

Learner Scenario

Mary Smith wants to be a biology major and is entering her freshman year at State University, where Mr. Mathlet coordinates introductory courses. It is the start of the school year, and he has almost ten thousand new students to assign courses to. He sees that Mary has an interest in biology, so he assigns her to take the State University Biology Calculus pathway to complete in the first academic year.

After Mary gets the registration e-mail, she navigates to the GLP website. She creates a learner account and is presented with several different learning materials about trees—this is a basic test for her learning style preference and not directly related to the calculus topics she will be learning. One example shows her a small video and some graphics, another is a text passage describing the same information, and a third is an audio recording of a botanist in the field describing a rain forest. GLP asks Mary which option she preferred, and she selects the visual category. GLP will initially recommend more visual nuggets to her, but it may adjust the recommendations as it learns more about her learning habits.

Mary also has a chance to list her non-academic interests. This information will help customize the problem sets and nuggets that GLP recommends to her, and it could be used to match her up with an on or off-campus learning community. She imports her Facebook² interests, which include jazz music, baseball, and action movies.

Benefits and Features

Individualized Learning Goals

Learners will be able to pick individual learning goals, which means they can focus on topics that interest them, instead of receiving a combination of possibly interesting and uninteresting material—for example, those interested in biology would learn calculus from a different perspective than those interested in theoretical mathematics. A learner can declare her learning goal in one of three ways. First, she could pick a topic from the topic map (i.e. *derivatives*). Second, she could indicate a general field of interest (i.e. introductory biology calculus). Third, she could participate in an educator-defined class, as Mary does in our story. GLP uses the learner's goal to refine the scope of her content map.

Engaging Learners Through Interests

Once GLP knows what a learner wants to master, it uses its knowledge of the learner's interests to keep her engaged with personalized material. For example, GLP may use her non-academic interests to tailor the learning nuggets and better engage her, which has shown to improve algebra learning gains (Walkington, 2013). If she is a Boston Celtics³ fan, she may be recommended more basketball or Celtics related nuggets. Each learner embodies a set of inherent attributes that defines her needs and the context of her learning. Other examples of these attributes include learning goal, major field of study, preferred interface style, preferred learning style, and previous knowledge.

GLP determines these learner attributes at registration and through continuous learner analytics. A questionnaire or a basic assessment test could determine things like preferred learning style or non-academic interests. As GLP gathers more information from learners and

² Facebook, Inc., <http://www.facebook.com>

³ Celtics Basketball, L.P., <http://www.nba.com/celtics/>

analyzes each individual's learning patterns, it can refine the learners' attributes. GLP may notice that parameters like her preferred learning style (i.e. visual, textual, or auditory) or even her preferred interface style (i.e. node-based, virtual world) have changed. For example, a learner may claim a preferred learning style of visual materials, but GLP notices that she actually performs better when using auditory *materials and adjusts her preferences automatically*.

Differentiated Instruction With Learning Styles

GLP could enable differentiated instruction through its knowledge and application of learning styles. Differentiated instruction provides each student with different ways of understanding concepts appropriate to each one's ability, as well as assessing each student according to her ability (Tomlinson, 2000; McQuarrie, McRae, & Stack-Cutler, 2008; CAST, n.d.). Tomlinson describes four ways differentiation can be achieved: 1) content, 2) process, 3) products, and 4) learning environment. GLP could use its learner data, such as preferred learning style, to differentiate among all four methods, to differing degrees. While some researchers debate if learners should follow a single learning style, GLP could use its learning style data to encourage diversity in nuggets used, instead of limiting learner choice to a single style (Pashler, McDaniel, Rohrer, & Bjork, 2008; Glenn, 2009; Holden, 2010)

Software Application Descriptions

In this section we present eight software applications for GLP. Each one embodies a set of functionality to improve the learning experience. For each app, we provide a description, a learner scenario, and its main benefits and features.

User Visualization

Description

User visualizations display the content map and nugget data in ways that are intuitive for each learner. These could range from geographic to node-based to 3D virtual world visualizations. For example, for geographic interfaces, a content map might be overlaid onto the United States with cities representing each topic, and nuggets might be mapped to rooms inside a building within the city. In this case, Cleveland might be where learners study *derivatives*, and Progressive Field®⁴ might house all of the nuggets classified as lecture notes, with different seating sections representing different majors (odd sections contain *biology* notes, while even sections contain *engineering* notes).

Learner Scenario

After importing her Facebook interests, Mary selects a visualization style. GLP offers some pre-defined categories, including geographic, node-based, and 3D virtual world. Since Mary enjoys geography, she selects the geographic option. GLP knows that she has an interest in baseball, so it uses a baseball overlay on top of a geographic visualization. For the high-level topic visualization, GLP starts her off with a trip around the U.S.A. and asks her to visit all the Major League Baseball®⁵ stadiums with a general East-to-West direction of travel. She sees the map from Figure 1, which shows different topics in biology calculus overlaid onto baseball stadium locations.

⁴ Progressive Casualty Insurance Company Corporation, <http://www.progressive.com>

⁵ Major League Baseball Properties, Inc., <http://www.mlb.com>



Figure 1. Example of Geographic User Interface (original image courtesy of National Atlas (National Atlas of the United States, 2003))

Earlier in the afternoon, Mary had chatted about GLP with a new friend, Mark, who is also a freshman at State University. Mark prefers simple interfaces when he works on the computer, and he selected a node-based interface. Mary appreciates that she selected an interface that would be more dynamic and engaging for her.

Benefits and Features

Independent Visualizations of the Same Activity

Learners each view independent and personalized visualizations of the same activity, even if they interact with each other synchronously. For example, John and Mary might both prefer geographic interfaces, but John likes soccer and Mary likes baseball, so John’s content topics map to soccer stadiums while Mary’s map to baseball stadiums. When they both study *derivatives*, each would see a different sports stadium, even though the underlying materials are the same. A modern example of this is the individual views that people see in massive online games like World of Warcraft®.

Geographical Visualization

In this report, we use a geographical visualization in the learner scenarios to demonstrate many of the features designed to engage learners. Spatial metaphors for complex information systems have been explored before, especially in terms of adaptive hypermedia in information retrieval—in research studies, their efficacy depends on the actual implementation. We believe that, if implemented well, they could help some GLP learners; we also recognize that some learners may find the spatial metaphor distracting and select other visualizations. Studies show that people can retrieve information faster and more accurately when it is mapped to a physical representation (Ark, Dryer, Selker, & Zhai, 1998; Ingram, Benford, & Bowers, 1996). Some researchers specifically propose a city metaphor to represent non-spatial data (Ingram, Benford, & Bowers, 1996; Dieberger & Frank, 1998). While the research focuses on information retrieval instead of “learning,” these geographical interfaces may prove useful to some learners in

⁶ Blizzard Entertainment, Inc., <http://www.blizzard.com>

recalling past knowledge learned in GLP (i.e. “I remember studying this in Cleveland!”). Researchers note that adjustment to a spatial representation may take some time until learners gain familiarity with it (Jones & Dumais, 1986).

Content Map

Description

Content maps allow learners to study topics in a non-linear fashion, since the maps connect conceptually related topics to each other in a directed graph. This idea is similar to *learning trajectories* in youth math education and research, or the ASSISTments®⁷ Skill Diagram (Daro, Mosher, & Corcoran, 2011; Hefferman, Hefferman, & Brest, n.d.). From the Khan Academy Knowledge Map, we derive a concrete example: learning *Fractions* does not depend on knowledge associated with *Exponents*, so the two concepts could be learned in any order; the reverse example would be that *Addition and Subtraction* is a pre-requisite for *Multiplication and Division*, so these topics must be learned sequentially (Khan Academy, n.d.).

Learner Scenario

GLP analyzed the learning goals that Mr. Mathlet assigned to Mary. It determined that she needs to master a set of topics from the calculus content map—the blue and red arrows in Figure 2 represent two different *pathways* within biology calculus that both allow her to achieve her learning goals. Table 2 shows one possible topic mapping for the blue pathway, using data from MIT Crosslinks (MIT, n.d.). Based on the popularity rating of the blue pathway, she chooses to follow it—if it does not seem to be effective, she can always change later.



Figure 2. Example Geographic GLP Interface (original image courtesy of National Atlas (National Atlas of the United States, 2003))

⁷ Carnegie Mellon University, <http://www.cmu.edu>

City	Team	Crosslinks Topic
Tampa Bay	Rays® ⁸	Functions
Atlanta	Braves® ⁹	Derivatives
Kansas City	Royals® ¹⁰	Quotient Rule
Houston	Astros® ¹¹	Differential
Phoenix	Diamondbacks® ¹²	Antiderivative
Anaheim	Angels® ¹³	Ordinary Differential Equation

Table 2. Blue Arrow Mapping to MIT Crosslinks

Mary then gets a short assessment test to determine where on the blue pathway she should start. GLP finds that in some topics, Mary is actually at an intermediate level, while in others she is at a basic level. She has not mastered any topics yet. GLP places her at the start of the blue pathway.

Benefits and Features

By focusing the content map on topics instead of “classes,” GLP offers a more comprehensive view of an entire domain, not just a single course. For example, GLP could include all calculus topics, not just those found in Calculus I. Furthermore, topics allow learners to relate knowledge between disciplines. Physics and calculus share many of the same topics, and in a content map a learner could more easily see how the two domains are conceptually related.

In order to construct these maps, GLP will store topics individually instead of aggregated into a “course.” Each content topic will have its own metadata, which includes information like a topic name, a description, keywords, a rigor level, relevant major(s), pre-requisite topics, and mastery level(s) for pre-requisite topics.

Customized Maps Per Major

For topics that are common to multiple domains (i.e. *derivatives* are used in calculus and physics), they can be grouped together to form major-specific content maps. Tailoring subjects like mathematics to engineering has been shown to improve student engagement and retention at several universities (Lord, 2012). The National Research Council’s (NRC) BIO2010 report also supports the idea of specialized math; in the report, the NRC recommends specific mathematics requirements for an undergraduate biology curriculum (Committee on Undergraduate Biology Education to Prepare Research Scientists for the 21st Century, 2010). Thus, in GLP, “engineering calculus” could include different topics than “biology calculus.”

⁸ Tampa Bay Rays Baseball Ltd., <http://tampabay.rays.mlb.com>

⁹ Atlanta National League Baseball Club, Inc., <http://atlanta.braves.mlb.com>

¹⁰ Kansas City Royals Baseball Corporation, <http://kansascity.royals.mlb.com>

¹¹ Houston McClane Company, Inc., <http://houston.astros.mlb.com>

¹² AZPB Limited Partnership, <http://arizona.diamondbacks.mlb.com>

¹³ Anaheim Angels, L.P., <http://losangeles.angels.mlb.com>

Updating Content Maps

While initial content maps could be designed by domain experts and would share many characteristics of instructional planning, GLP maps allow for more consideration of learner feedback. Instructional planning is the process whereby a teacher decides what material to cover, how much time to spend on each topic, and what resources are available—all in the context of what is appropriate for his specific class (Airasian, Engemann, & Gallagher, 2007). However, every learner learns differently, so while what the teacher creates may be appropriate for the majority of learners, it may not work for every learner (Fischer, Rose, & Rose, 2006). Topic-based content maps give GLP the ability to solicit learner feedback and update the maps accordingly.

Explicit learner feedback could be used to modify the maps. One example of this is video annotations, such as how Harvard Medical School's¹⁴ / Boston Children's Hospital's OpenPediatrics¹⁵ project allows users to annotate and comment on video lectures (OPENPediatrics, n.d.). As learners note areas of confusion and add external resources to clarify a topic, others can comment on the usefulness of these resources. Topics can then be divided into sub-topics to create a more detailed content map. At the university level, MIT Crosslinks provides another example of enabling learner updates (MIT, n.d.). Crosslinks is a content map of calculus topics, where learners are encouraged to contribute changes via a wiki format. A portion of the Crosslinks data is shown in Figure 3 in a node-based format.

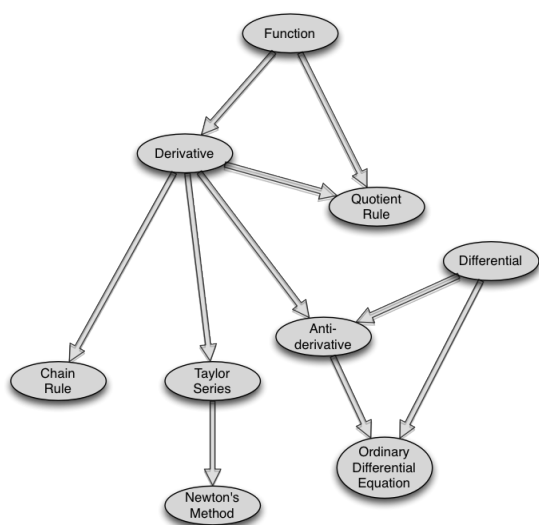


Figure 3. Node-Based Representation of Subset of MIT Crosslinks Data

Indirect ways to update these maps are also possible, such as through learner analytics of topic sequences. One can imagine that GLP offers different topic sequences to different learners, and the platform uses their learning results to determine sequence effectiveness. It can then update other learners' maps. While the general principle of different learning pathways for individuals has been demonstrated (Fischer, Rose, & Rose, 2006), GLP could enable more research in this area.

¹⁴ President and Fellows of Harvard College Corporation, <http://www.harvard.edu>

¹⁵ Children's Medical Center Corporation, <http://www.childrenshospital.org>

Some researchers have suggested another way to use analytics to improve course content. García et al., report on a tool that provides teachers with analyses of courses (García, Romero, Ventura, & de Castro, 2009). This tool evaluates student outcomes against association rules, which are given a rating for “interestingness.” These rules are teacher-constructed and relate course components to student outcomes. One example is “high homework scores but low final exam score means homework sets are too easy.” Teachers can then address the more “interesting” rules in their classes. GLP builds upon this by automating the feedback and improvement process, and applying the necessary changes only to individual learners. Instead of the course changes affecting all learners, only those who would perform better would see the changes.

Measuring Topic-level Mastery

Topic-based maps allow fine-grained assessment of learner knowledge, instead of broad generalizations of knowledge, spread over an entire course. These assessments are symbolized by the pre-requisite linkages between topics—learners must demonstrate a suitable level of mastery in the pre-requisites before studying a topic. This mastery level could differ for each type of learner, depending on individual needs. Bloom’s Taxonomy is well established in the education field, and it offers a standard dictionary for assessing learning (Anderson, et al., 1956). Basic knowledge and fact recall compose the most basic type of learning goal; higher-level goals include applied use of concepts in solving novel problems, and critically evaluating ideas for their merits and demerits. Anderson (one of Bloom’s students) and Krathwohl (one of Bloom’s original co-authors) crafted a revised version that uses action verbs to describe each level of learning goal—GLP assessments should follow this convention when evaluating mastery (Anderson & Krathwohl, 2001). Forehand lists the verbs that Anderson and Krathwohl describe in their book (Forehand, 2005):

Remembering: *Retrieving, recognizing, and recalling relevant knowledge from long-term memory.*

Understanding: *Constructing meaning from oral, written, and graphic messages through interpreting, exemplifying, classifying, summarizing, inferring, comparing, and explaining.*

Applying: *Carrying out or using a procedure through executing, or implementing.*

Analyzing: *Breaking material into constituent parts, determining how the parts relate to one another and to an overall structure or purpose through differentiating, organizing, and attributing.*

Evaluating: *Making judgments based on criteria and standards through checking and critiquing.*

Creating: *Putting elements together to form a coherent or functional whole; reorganizing elements into a new pattern or structure through generating, planning, or producing.*

Since majors might have customized content maps, one can imagine that they also have customized mastery levels for each topic. Biology majors might need to master *derivatives* at only an application level, whereas engineering majors might need to master it at a synthesis level. This will be reflected behind-the-scenes in how GLP allows different learners to progress through their content maps.

Pathways

Pathways are sub-sections of the content map that show learners which topics they need to master to achieve their learning goals. These pathways could be pre-defined by domain experts or determined by GLP based on aggregated learner history. A learner thus has many pathway options, even for a single learning goal. For example, there could be multiple “introductory biology calculus” pathways, each defined by different experts. Furthermore, each pathway could act as a modifiable template for an individual, where learners could add topics to the template.

The first step in selecting a pathway is for a learner to state a learning goal. She can do this by selecting a specific topic (i.e. *derivatives*), or a general domain (i.e. introductory biology calculus). She can then select from the different pathway options in GLP. All pre-requisite topics to support her learning goal are automatically included.

For educators who use GLP for a class, they could define a class pathway. They could then operate GLP similarly to a MOOC, where learners move through the content as a cohort. Learners would be able to add topics according to their interests, but would need to complete the “minimum” pathway set by their teacher.

Determining a Learner’s Starting Point on Her Pathway

When she registers, the learner takes an assessment test to determine her placement on her pathway and to assess which topics she has mastery knowledge in. The results could mean she starts at the very beginning of her pathway or partway through. The exact starting location depends on each learner’s previous knowledge level. It will be assumed that if a learner tests out of a topic, she has mastery of the pre-requisites. If it is later discovered that she is weak in a specific area or needs additional mastery, GLP can add topics to the learner’s pathway and reinforce her knowledge.

Content Recommendation Algorithms

Description

Content recommendation algorithms determine which topics a learner is prepared to study on her pathway. One example of this in an online context is the ELM-ART project, which shows learners which topics they are prepared for and which ones they should study later, through a traffic light graphic (Brusilovsky, Schwarz, & Weber, 1996). GLP combines this idea with a personalized content map and graphical representation of the topics. This visualization gives learners a better sense of which topics are related to which other ones, in addition to which topics they are prepared to study.

Note that two “levels” of recommendation algorithms will be used by GLP: a high-level one for the content topics, and a lower-level one for the nuggets. Different types of algorithms are needed at each level. In this section we focus on the topic-level algorithms, and later we will discuss the nugget recommendation algorithms.

Learner Scenario

Since Mary selected the blue pathway, GLP determines the topics she can study. However, during her assessment test, Mary did not achieve mastery in any topic, even though she did demonstrate knowledge in some of the basic topics like *Derivatives* and *Functions*. As a result, GLP searches for topics with no pre-requisites that Mary can start with.

GLP finds two topics along the blue pathway with no pre-requisites—*Functions* in Tampa Bay, and *Differential* in Houston. It presents both options to Mary. She still remembers some of the concepts in *Functions* from her high school class, so she decides to visit the Tampa Bay Rays and Tropicana Field®¹⁶.

Benefits and Features

The high-level content topic recommendation algorithm identifies the content topics that remain unmastered on the learner’s pathway and that she is prepared to study. A learner is prepared to study a topic when she has mastered all the pre-requisites, or if the topic has no pre-requisites. The learner can also ignore the recommendation algorithm and follow her self-interest—she can choose to study topics outside of her pathway. However, she will still need to honor pre-requisite relationships.

Learning Nuggets

Description

Learning nuggets are learning materials that teach a single topic, and they are recommended to learners based on potential usefulness in improving knowledge mastery (this recommendation process is described in Nugget Recommendation Algorithms section). Nuggets could include applets, simulations, case studies, example problems, lectures notes, media (video, audio, etc.), homework assignments, and assessment tools that are crowdsourced from public contributors as Open Educational Resources (OER). Though nuggets will be categorized into these types, they could also each represent different pedagogical learning styles—note that this means a video-based resource could be suitable for a learner with a visual, textual, or auditory learning style, depending on its characteristics.

Learner Scenario

Mary selected to first visit the Tampa Bay Rays and Tropicana Field, where she will study *Functions*. Entering the stadium, she sees that different sections contain different rigor levels and types of nuggets. The **Box Suites** are undergraduate interactive applets, the **Lower Deck, First Base** seats are graduate lecture notes, and the **Upper Deck, Third Base** seats are undergraduate case studies. There is one nugget per seat, so she has a wide variety of options to choose from. As she wanders through the Lower Deck, Third Base seats, metal placards on each seat flash at her. Each placard contains a phrase or keyword, and each seat seems to have at least four placards attached. Mary stops at one seat, and she sees: “Creator: John Smith” “population growth” “video” “visual” “4.2 stars”.

Benefits and Features

Learner Choice of Nuggets

Learners will be able to choose which nuggets they actually study. GLP will have a large number of nuggets, and learners can study as many nuggets as they want, above a required minimum, before taking a topic assessment. If learners prove their mastery of the topic, they can select another topic to study. If not, they will be presented with a re-ranked list of nuggets for the same topic so that they can try additional learning materials. To illustrate this, *derivatives* is a fundamental concept for calculus.

¹⁶ Tropicana Products, Inc., <http://www.tropicana.com>

The nuggets within this topic might be categorized as seen in Figure 4. Nuggets within one of these categories might look like the example in Figure 5.

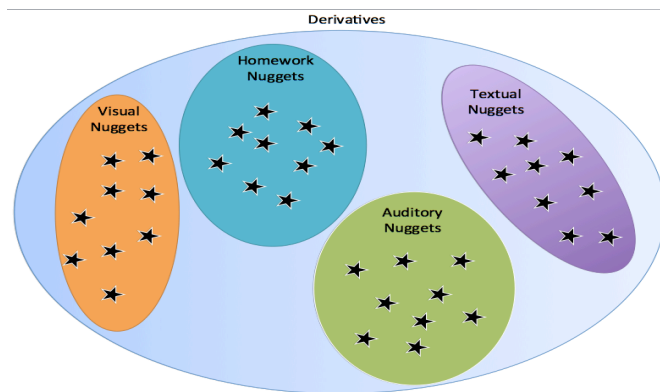


Figure 4. Learning Nugget Categories in Derivatives

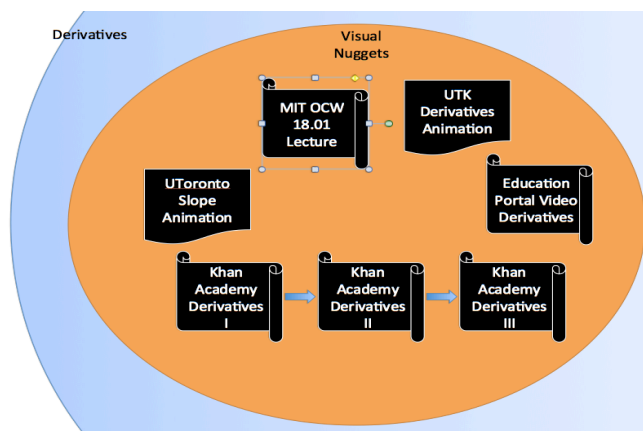


Figure 5. Example of Visual Learning Nuggets for Derivatives

Nugget Metadata

To match nuggets to learners, nuggets need to be tagged with metadata. These attributes could be included by the original content creator, added by learners, or calculated by GLP. Some examples include learning style fit, non-academic keywords, relevant major(s), rigor level, and an effectiveness rating. Nugget pre-requisites could also be specified, if they build upon knowledge or examples in other nuggets.

Non-disruptive Addition of Nuggets

Adding new nuggets should not disrupt the learner experience. Given the open nature of GLP, we expect that content creators will continuously upload new nuggets. These nuggets will seamlessly integrate into the nugget recommendation algorithms in real-time so that learners can use them—even if the learners have already started learning the related topic.

As third-party contributors create and add nuggets to GLP, learners get presented with more choices in “real-time”, as shown in Figure 6.

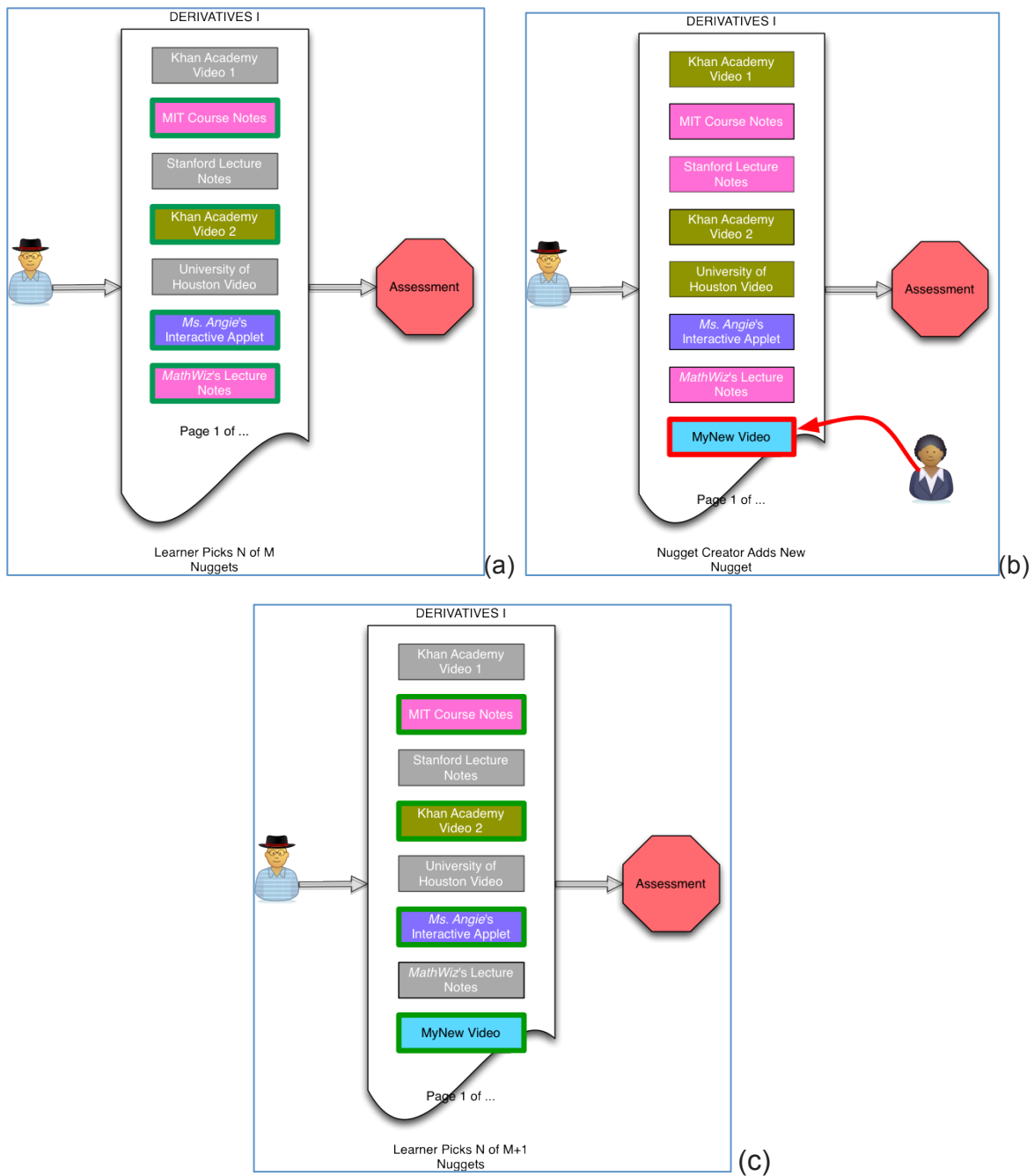


Figure 6. (a) Learner Selects N of M Nuggets to Study. (b) Adding a New Nugget Does Not Interrupt Learner Progress. (c) Learner Selects From Larger Pool of Nuggets.

Nugget Recommendation Algorithms

Description

For the lower-level nugget recommendation algorithms, GLP combines the nugget metadata with learner attributes and histories to create personalized rankings of each nugget for each learner. A simple version of this type of personalization has shown useful in promoting transfer and future learning for algebra (Walkington, 2013). Over time, if a nugget proves more useful for a subset of learners, GLP will recommend that nugget more often for other learners with similar backgrounds. However, if a nugget proves less useful or detrimental to a subset of learners, GLP will either not recommend the nugget for that subset of learners or remove it from the data repository.

Learner Scenario

Mary stops her random exploration of Tropicana Field and pulls up GLP's recommended nugget list. She sees that there are over ten pages of *Function* nuggets available in the stadium; the first page includes a mixture of nuggets from the Right Field bleacher seats, the Lower Deck, First Base side, Lower Deck behind home plate, and the Box Suites. She is free to explore these in any order, or even to skip to later pages on the list. However, she knows that GLP produced this list just for her, based on her interests, background, and other learners' usage of the nuggets.

Mary decides to pick nuggets from the first page. She wanders over to the Right Field bleacher seats to read some undergraduate lecture notes from MIT, then heads over to the Upper Deck, Third Base Side to analyze an undergraduate level case study from Stanford. Finally, she plays with some undergraduate level interactive applets in the Box Suites made by *MarineBiologist123*, a practicing biologist. Mary loves exploring Tropicana Field while learning more about *Functions*!

Mary feels like she has a good grasp of *Functions*, so she returns to the ticket office and asks for an assessment test.

Benefits and Features

Improved Learning Outcomes

Researchers have found that different types of recommendation algorithms can improve learning outcomes. Some techniques they have tested include collaborative filtering, preference-based, neighbor-interest-based, and other data mining techniques; some have tested with simulations, while others have performed field studies (Hummel, et al., 2007; García, Romero, Ventura, & de Castro, 2009; Farzan & Brusilovsky, 2006; Recker, Walker, & Lawless, 2003; Romero, Ventura, Delgado, & De Bra, 2007; Tsai, Chiu, Lee, & Wang, 2006). For example, Nadolski et al. have used simulators to test personalized recommendation algorithms for lifelong learners and self-organized learning networks (similar to our learning nuggets) (Nadolski, et al., 2009). We created a simulation platform based on cognitive tutor technology to compare nugget recommendation algorithms; preliminary results have been presented (Wang, Shaw, Larson, & Uchino, 2013).

Example of Weighted Ranking Algorithm

One envisioned method of ranking the nuggets for a specific learner uses a weighted combination of the learner's preferred learning style (i.e. visual nuggets), personal interests (i.e. baseball), and a rating that encompasses the historical data about each nugget. After using this weighting to score all nuggets in the topic, GLP presents the nuggets in descending order of score, much like a search engine's results page—new (or “unranked”) nuggets could be strategically inserted into the list so that learners use them and help them develop a rating. Similar to a search engine's results, this list of nuggets will differ between individual learners. From this list, the learner can then select and study as many nuggets as desired, in any order.

Advanced Weighting Algorithms

More sophisticated versions of this algorithm could also be imagined, where the weighting is dynamic and depends on other factors: 1) Different nuggets may be more useful at the start of a learning sequence (when topic mastery is low) and others at the end (when topic mastery is high, and only some details are unclear); 2) A specific sequence of nuggets may be more useful than a single nugget.

Furthermore, GLP could adjust the weightings to encourage differentiated instruction, instead of limiting learners to a single learning style. For example, if a learner has a high preference for visual nuggets, consistently selects videos and visual nuggets, yet performs poorly, GLP might introduce a variety of other learning styles or types of nuggets—pushing visual nuggets lower in score. Thus the learner would get a variety of explanations and viewpoints for explaining the concept, which would match the differentiated instruction philosophy (McQuarrie, McRae, & Stack-Cutler, 2008; CAST, n.d.; Tomlinson, 2000).

Intelligent Tutors

Description

Intelligent tutoring systems have been developed since the 1980s and thus offer several decades of research results and technology from which to build (D'Mello, et al., 2010; Corbett & Anderson, 1995; Brusilovsky, Schwarz, & Weber, 1996; Baker, et al., 2006). Tutors are created with a cognitive model of “expert knowledge”; as learners use the tutors and solve problems, the tutors also build a real-time model of “student knowledge.” Tutors give hints and problems to move the student models closer to the expert models, and they try to correct misconceptions; some even detect learner emotions to determine when hints are needed (D'Mello, et al., 2010). While some criticisms of tutor efficacy exist (What Works Clearinghouse, 2010), researchers continue to improve intelligent tutors.

Within GLP, tutors could be integrated into several of the other software applications. They could be used in homework nuggets, to provide formative assessment, or they could be used in formal assessments to measure topic mastery.

Learner Scenario

Mary starts working on the *Functions* assessment. The assessment focuses on application of her knowledge of *Functions*, instead of just simple regurgitation of content facts or equations. She starts the first problem, but doesn't understand how to get past the second step. She requests a hint, an action that GLP records. Mary gets past her mental block and finishes the first problem. She works on the other problems and also uses some hints to get through them.

She marginally fails the assessment at the end, and the ticket office asks Mary to return to the stadium and try some more nuggets.

Mary re-opens up the GLP recommendation page and sees a new list of nuggets to try—the list has been updated with additional information from other learners and her recent assessment results. GLP follows a mastery learning philosophy and expects all students to master each topic before moving on to subsequent topics. Since *Functions* is a fundamental concept for the rest of Mary's pathway, GLP expects her to achieve at least an “*evaluating*” mastery level with it. The system also makes an internal note that Mary failed her assessment after using the three nuggets and adjusts their ratings accordingly.

This time Mary selects a Khan Academy video nugget from the Lower Deck, Third Base Side that is also highly recommended, but it doesn't match her visual learning style. After watching the video, she returns to the ticket office and asks for another assessment. This time she passes the assessment. Internally, GLP makes a note of this in Mary's learner record and also adjusts the Khan Academy nugget's rating appropriately. According to GLP's internal model of Mary's knowledge, it thinks she has achieved “*evaluating level*” mastery (sufficient for biology majors) and marks the topic of *Functions* as “completed” on her records. GLP now permits her to leave Tampa Bay.

Mary returns to the GLP main page and sees the content map with her pathway. Tampa Bay appears green, and the line connecting Tampa Bay to Atlanta is now bright, showing her additional stadiums that she can visit. Mary is prepared to visit Houston (*Differential*) or Atlanta (*Derivatives*) as her next stop.

Benefits and Features

Through this formative assessment and feedback, tutors can identify in which areas a learner is missing knowledge or ready to move on. If a tutor believes that a learner has mastered a topic to the sufficient degree, she is allowed to move on to subsequent topics. On the other hand, if a learner is not ready to move on, a tutor can then feed information on weaknesses back to GLP's nugget recommendation algorithm and improve the types of nuggets that GLP recommends. For example, GLP could determine that a learner needs additional help in a sub-topic of *derivatives*, or that the learner has trouble applying the idea of random numbers to population ecology. GLP could then recommend specific nuggets that target these weaknesses or even add certain topic nodes to her pathway to reinforce the learner's knowledge.

Learning Communities

Description

Learning communities provide opportunities for learners to bond with and collaborate with peers, which inherently occurs in traditional classrooms. Even though GLP will be an asynchronous platform, the social aspect remains integral. Research has shown that learners who teach and help other learners to understand material themselves master a topic better (Lenning & Ebbers, 1999). As it is often said, “Teaching is a learning experience.”

Learner Scenario

Mary travels to Atlanta, and when she arrives at Turner Field¹⁷, she finds a group of five avatars standing outside of the park. She introduces herself to them—David, Marcus, Stella, Alexandra, and Sebastian. Through some quick chatting, she finds that they are from all over the world, and her excitement level shoots up! Each of them is also using the GLP platform to study mathematics. Some are in university like her, while Sebastian needs to review the topics for his job. Stella actually studies in high school in Taiwan, but her school does not offer advanced mathematics courses, so she turned to GLP. GLP has recommended that these six learners study *Derivatives* together, and they will be able to communicate and collaborate once they enter the stadium. Unbeknownst to Mary, each of her study partners sees their “GLP world” differently, and in fact she is the only one that sees a baseball stadium. The others are looking at other representations of the topic, such as simple node maps or more elaborate virtual worlds.

The six new friends enter the stadium, and each pulls up his or her personalized list of recommended nuggets. Mary wanders over to the Upper Deck, First Base side to try some simulations. She hears her cell phone ring—text message! Sebastian asked the entire group a question about some exercise problems, to see if someone could help him get unstuck. Mary remembers some hints that her high school teacher had given her about the concept and replies to his text message.

After using some simulations and then reading some lecture notes in the bleacher seats, Mary returns to the concourse. She sees a large screen in the middle of the concourse with some notes from her friends.

Try MathWiz’s video on slopes—awesome! Section 212, seat 5. Stella.

Loved MIT OCW notes on derivatives—clear and concise. Section 134, seat 16. Marcus.

Mary thought that one of the simulations that she used was pretty good too, and it might be helpful for Alexandra since she wanted to be a math teacher. Mary adds her own recommendation onto the screen.

Benefits and Features

Open Learning Communities

Many types of open learning communities will exist for all GLP users. Forums and community sites will allow for learner-learner interaction, and it could be envisioned that learners self-organize local meet-ups, as has happened in existing MOOCs (Pokross, 2012). Remote study groups could be facilitated by web videoconferencing technologies. Other types of group communication and collaboration technologies could also be used, such as real-time collaboration tools / white-boards, video annotations (Vialogues (Vialogues, n.d.)), wiki’s, shared bookmarks, or small group tutoring spaces. These communities could consist of not only other learners (as in the OpenStudy¹⁸ model (Open Study, n.d.)), but also live human tutors who interact synchronously with the learners in private tutoring sessions.

¹⁷ Atlanta National League Baseball Club, Inc., <http://atlanta.braves.mlb.com>

¹⁸ OpenStudy Corporation, <http://www.openstudy.com>

Cohort-based Learning

While some of these communities might be open to everyone, others might be restricted to smaller cohorts that move together, like what we saw in Mary's story. For example, this type of app could recommend study partners and small learning communities based on each learner's strengths, weaknesses, learning styles, and levels of content mastery. These cohorts could then move through the material at the same pace and support each others' progress. This could help facilitate better learning for each individual in the study group as well as improve overall group performance.

Nugget Rating Algorithms

Description

Nugget rating algorithms synthesize how useful nuggets have been in improving learners' knowledge, by calculating a rating for each nugget. These ratings are derived from trends in learner data, such as learner performance in assessments, forum participation, and nuggets used. For example, GLP may identify that a visual nugget about irrational numbers created by Khan Academy proves very useful to underclassmen studying economics and interested in basketball, so it gets assigned a high rating for that type of learner. An MIT BLOSSOMS nugget on the same topic might be more effective for high school students interested in engineering and nature, and it would get assigned a low rating for upperclassmen economics majors who like basketball, but a high rating for high school students interested in engineering and nature.

Learner Scenario

After Mary took the two *Functions* assessments in Tropicana Field, GLP looked to see who else had used the same four nuggets. It found that thousands of other learners have taken one, two, three, or even all four of the same nuggets. GLP analyzed their assessment results along with Mary's and estimated the percentage contribution of each individual nugget to her overall knowledge gain.

GLP finds that while Mary had failed her first assessment (and it had originally decreased the ratings for the first three nuggets she used), adding her second assessment and recalculating with other learners' data showed that the interactive applet from *MarineBiologist123* contributed the most to her learning. Many other GLP learners also had strong gains from this applet, regardless of the other nuggets that they used or of their individual backgrounds. And even though Mary passed the second assessment after reviewing the Khan Academy video, it corrected a minor misconception instead of giving her new, basic understanding. Thus GLP readjusts the nugget ratings (which range from 0 to 10)—it changes the rating for *MarineBiologist123*'s applet by 0.25 points, the rating for MIT lecture notes by -0.1 points, the rating for Stanford's case study by -0.1 points, and the rating for the Khan Academy video by 0.05 points. This information will be used in the future by the nugget recommendation algorithms and will be most heavily weighted for learners similar to Mary.

Benefits and Features

These algorithms take advantage of the large numbers of learners to detect the impact of individual nuggets. Even though learners may decide to use several nuggets before taking an assessment, advanced statistical analyses could tease out individual nugget impact. The large number of learners will also enable these algorithms to filter out the effects of external factors. For example, learners may acquire additional knowledge outside of GLP or be distracted by other life events, which may be inadvertently attributed to the nuggets that they used. Thus data

from a single learner would not significantly change a nugget rating; however, broad trends across many learners will influence nugget ratings.

Conclusion

In this section we presented a vision for Guided Learning Pathways (GLP), an asynchronous, personalized learning platform for both traditional and non-traditional learners. GLP emphasizes topic-based mastery and provides learners with recommended learning materials (nuggets) that help them achieve this mastery. GLP's service-oriented architecture enables easy upgradeability and flexibility, which allow third-party application developers to contribute to the platform. Data analytics throughout the platform also enable complete personalization for each learner.

To describe GLP's functionality, we describe the learners that GLP will serve and provide descriptions of eight potential applications: User Visualization, Content Map, Content Topic Recommendation Algorithm, Learning Nuggets, Intelligent Tutor Systems, Nugget Recommendation Algorithm, Learning Communities, and Nugget Rating Algorithms. For each app, we provide a learner scenario, benefits, and features.

3. GLP Core Software Architecture

Introduction

This section describes a technical framework and architecture to support the vision outlined in Section 2. The user interacts directly with various applications, each of which is supported behind-the-scenes by pre-defined GLP software services. These services give apps the ability to access and store data in a central data repository. The data in the repository, such as learner activity tracking, would be accessible to all apps, not just the one that collected it—this creates a powerful data aggregation feature within GLP.

By creating a two-layer architecture that separates apps from services from data, and providing a shared data repository, GLP enables flexibility and upgradeability for the entire platform. Core GLP developers can easily add new services or enhance existing ones, without disrupting the users. Third-party developers can creatively combine services and data to offer new value to users. With a variety of apps to select from, learners and educators will be able to personalize their experiences by “swapping out” apps in the same category. For example, one learner may prefer the nugget recommendation algorithms from MIT, while another may prefer those created by Stanford. This two-layer architecture is shown in Figure 7.

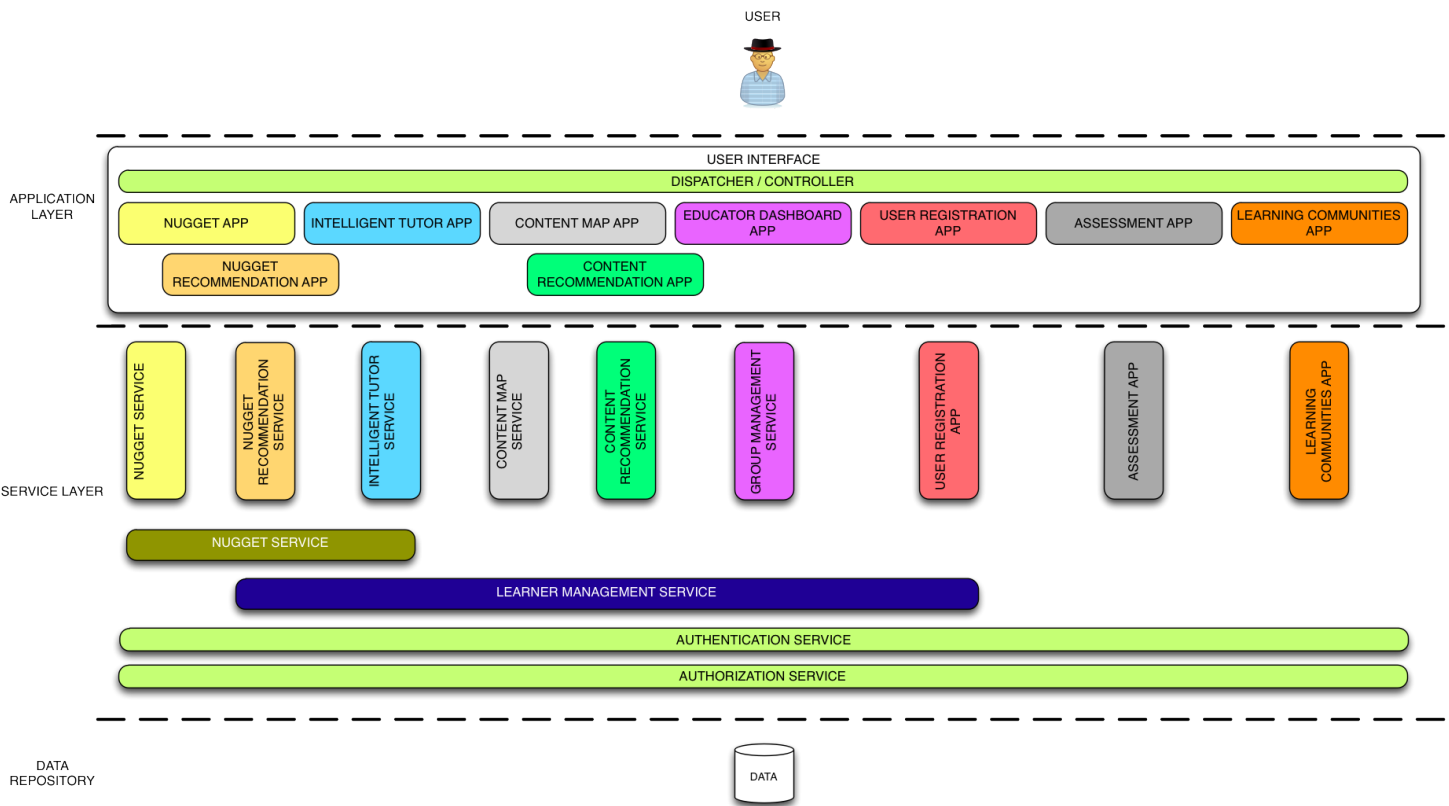


Figure 7. Two-layer Software Architecture for GLP

The remainder of this section is organized as follows: First, we describe the design process that we followed to define both the application layer and the service layer. Next, we provide more detail on the required functionality of each app in the application layer. We then show how the service layer can support the application functionality, through a discussion of conceptual data models and process flow models. Finally, we conclude with a discussion on how the service layer could be implemented using Open Service Interface Definitions, a service-oriented architecture for enterprise educational systems.

Design Process

Design Goals

To create an adequate system architecture, we first look at what the architecture has to achieve. As mentioned before, some of the goals are for GLP to be easily upgradeable and maintainable. This requires several things. First, the architecture must be technology-agnostic. In the future, developers will use other programming languages and data repository systems, and they must be able to interface with the existing GLP platform. Second, GLP components must be cleanly separated, with well-defined responsibilities and interfaces. This means that developers can easily change part of the platform with minimal impact on other parts. Cleanly separated interfaces also allow GLP to seamlessly add data repositories to take advantage of third-party resources.

At the application layer, process flow control needs to exist to guide the learner through the applications in a set order. For example, after selecting a topic to study, she is recommended some nuggets—this interaction requires process control to pass from one app (content map) to another (nugget recommendation). Not only does this sequencing need to be controlled, but it also needs a clearly defined interface to allow for app swapping. If a learner decides to use a different type of nugget recommendation application, it should interface correctly with her active content map application.

Selected Architecture

To achieve the design goals outlined above, we select a hybrid service-oriented and event-driven architecture. Jean-Louis Maréchaux describes such an architecture (Maréchaux, 2006):

Service-Oriented Architecture

SOA is an architectural concept in which all functions, or services, are defined using a description language and where their interfaces are discoverable over a network. The interface is defined in a neutral manner that is independent of the hardware platform, the operating system, and the programming language in which the service is implemented.

One of the most important advantages of a SOA is the ability to get away from an isolationist practice in software development, where each department builds its own system without any knowledge of what has already been done by others in the organization. This "silo" approach leads to inefficient and costly situations where the same functionality is developed, deployed and maintained multiple times. A SOA is based on a service portfolio shared across the organization and it provides a way to efficiently reuse and integrate existing assets.

Event-Driven Architecture

In 2003, Gartner®¹⁹ (see Resources) introduced a new terminology to describe a design paradigm based on events: Event-Driven Architecture (EDA). EDA defines a methodology for designing and implementing applications and systems in which events transmit between decoupled software components and services. EDA does not replace, but rather, complements the SOA. While SOA is generally a better fit for a request/response exchange, EDA introduces long-running asynchronous process capabilities. Moreover, an EDA node posts events and does not depend on the availability of a published service. It is really decoupled from the other nodes. EDA is sometimes also referred to as "event-driven SOA".

EDA uses messaging to communicate among two or more application processes. The communication is initiated by an "event". This trigger typically corresponds to some business occurrence. Any subscribers to that event are then notified and thus activated

We used the Kualii®²⁰ design process to create detailed models that fit the service-oriented part of this architecture (Quigley, 2009). Kualii is an open-source, service-oriented architecture used in higher education, and it has been tested and deployed by various institutions (Kualii Foundation, n.d.). Kualii's process shows that several models can be used to adequately describe a service-oriented architecture: 1) conceptual data process models to describe the data repository; 2) process flow models to show how services communicate with each other, apps, and the data repository; and 3) service definitions to define each service group.

To describe the event-driven application layer, we look at a generic publish-subscribe model. In modern web frameworks, a dispatcher or controller looks for publish messages (i.e. this app is done with its job—next app!) and know the appropriate follow-on app to call (Microsoft, n.d.; Spring, n.d.; Gervasio, 2010). In this fashion a learner experiences a seamless interaction with GLP, even though a dispatcher passes process flow to different apps for different functions.

Application Definitions

First, we define the types of applications that could interface with GLP and their functional requirements; we then define the services and data models needed to support each of these applications. For each application type, we define the type's functionality and its responsibilities through functional statements. These are shown for the following ten applications: 1) Assessment; 2) Learner Registration; 3) Content Map; 4) Content Recommendation Algorithm; 5) Intelligent Tutors; 6) Learning Communities; 7) Learning Nuggets; 8) Nugget Rating Algorithm; 9) Nugget Recommendation Algorithms; and 10) User Visualization.

¹⁹ G. G. Properties, Ltd., <http://www.gartner.com>

²⁰ Indiana University Research and Technology Corporation, <http://iurtc.iu.edu>

Assessment
Assess for prior mastery (over multiple topics)
Assess for topic mastery (single topic)
Identify areas of weakness

Table 3. Assessment Functional Statements

Learner Registration
Collect learning goal
Collect learner profile (name, e-mail, major, interests)
Perform learner preference assessments (GUI, learning style)
Assign to a class (if appropriate)

Table 4. Learner Registration Functional Statements

Content Map
Allow learners and domain experts to suggest new pre-requisites to existing topics
Maintain different maps for any given domain
Allow learners and domain experts to suggest new topics
Return pathway options for achieving a learning goal, within a specific map

Table 5. Content Map Functional Statements

Content Recommendation Algorithms
Examine learner's pathway for un-mastered topics
Check learner's mastery levels for pre-requisite topics
Check other learners' histories for learning gains associated with selecting a specific topic
Record learner's choice of topic

Table 6. Content Recommendation Algorithms Functional Statements

Intelligent Tutors
Request or detect appropriate difficulty level for learner
Present appropriate assessment problems to learner
When necessary, provide hints and explanations to learner
Identify areas of weakness or possible improvement
Modify learner's pathway as needed, to address weaknesses

Table 7. Intelligent Tutors Functional Statements

Learning Communities
Examine learning behaviors and preferences across multiple learners
Recommend or form learning communities based on ability and need
Detect learner doubts or learning needs
Detect learner contributions in helping peers improve understanding
Record analytical data about learner participation
Provides an area for collaboration and information exchange among learners
Recommend topics to study based on needs

Table 8. Learning Communities Functional Statements

Learning Nuggets
Display learning material to the learner
Detect learner interactions with the nugget
Utilize learner's preferred intelligent tutor (for homework nuggets)
Record learner interactions in the GLP data repository

Table 9. Learning Nuggets Functional Statements

Nugget Rating Algorithm
Examine overall learning gains for a learner after using a nugget
Examine learning gains of other learners when using the same nugget(s)
Estimate percentage of gain "due" to each individual nugget used by learner
Update internal nugget rating for each nugget used by learner; could be per "category" of learner

Table 10. Nugget Rating Algorithm Functional Statements

Nugget Recommendation Algorithms
Examine learner's history and profile for key attributes
Examine other learners' interactions and learning gains with each nugget in the relevant topic
Calculate potential learning benefit to the specific learner, for each nugget in the relevant topic
Display recommended nugget list to the learner
Record learner's choice of nugget
Request metadata for each nugget in the topic


Table 11. Nugget Recommendation Algorithms Functional Statements

User Visualization
Displays GLP content map to learners in preferred visualization method
Record analytic data about learner interactions with GLP

Table 12. User Visualization Functional Statements

Conceptual Data Models

High-level conceptual data models help the design of the data repository, although they do not get into the granular details of tables and fields (Quigley, 2009). These data models show the key attributes of each entity that are stored, as well as how different entities interact with each other. They are drawn from a system-wide perspective at a snapshot in time (as opposed to a single learner's viewpoint, for example). We use crow's foot notation in the models, a commonly used standard (Stewart, 2008).

Figure 8 offers an example of a conceptual data model. Rectangular boxes are entities, diamonds are actions, and circles are attributes. The symbols on either end of a connecting line signify the quantity of the relationship, i.e.  means "one or more." A summary of these symbols is provided in Figure 9.

Using them, you can then read a relationship in either direction, i.e. learners participate in zero or more learning communities, and the learning communities are used by zero or more learners. The tables at the bottom of each conceptual data model list attributes associated with each entity.

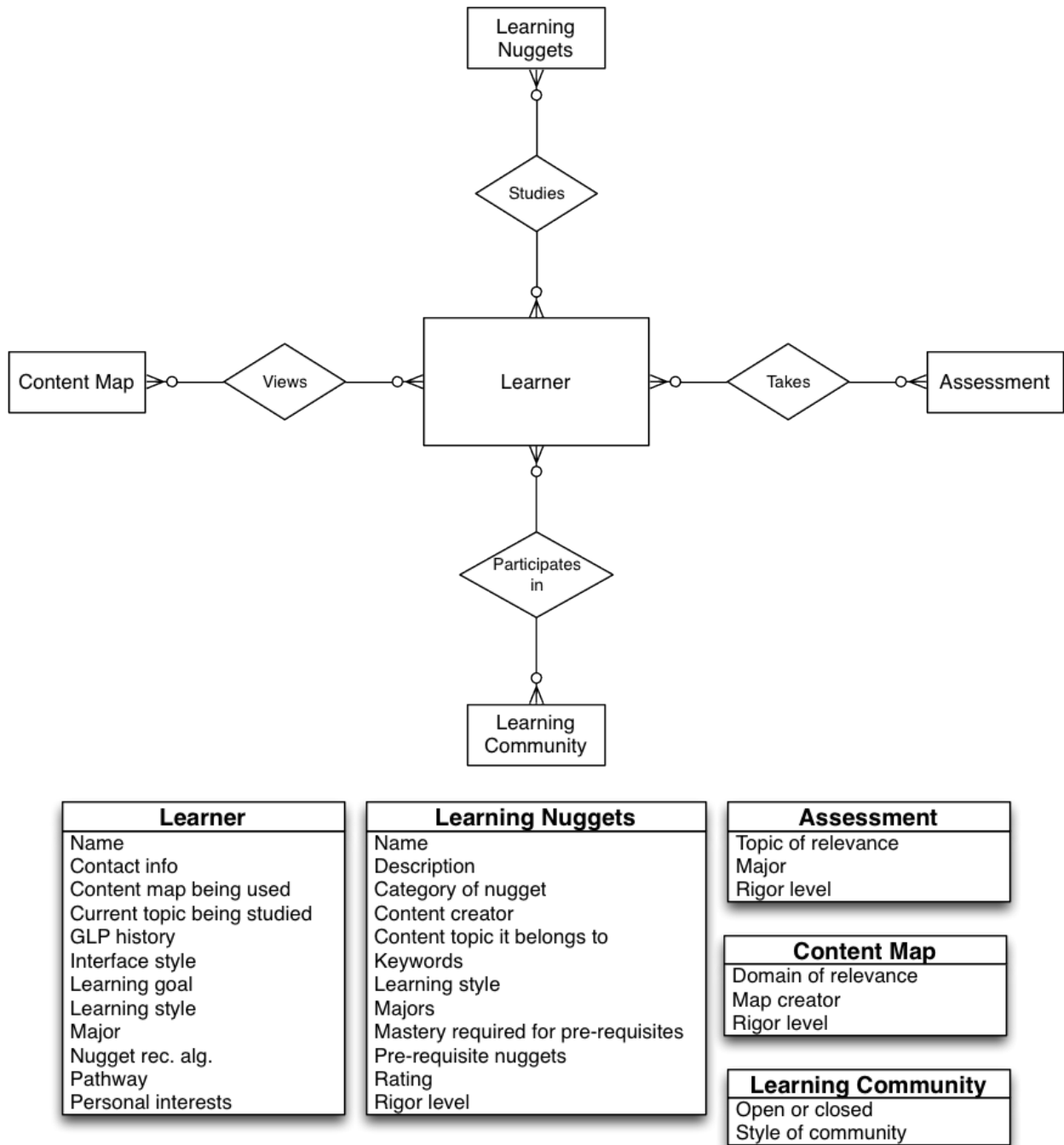


Figure 8. Conceptual Data Model for Learners

————	No relationship
—+—	One and only one
—>+—	One or many
—>—	Many
—+o—	Zero or one
—>o—	Zero or many

Figure 9. Summary of Crow's Feet Notation

We present conceptual data models for other entities in Figure 10, Figure 11 and Figure 12. While this set is not exhaustive (due to the incredible flexibility of the GLP platform), these models should be sufficient to build an initial platform. Developers can add more models to support new features, or modify these models as needed.

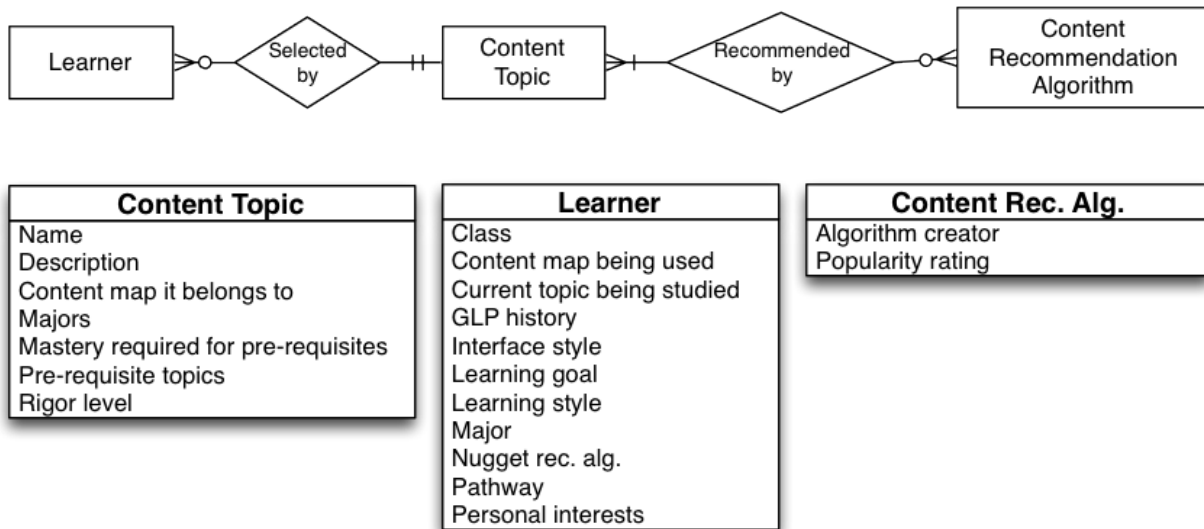


Figure 10. Conceptual Data Model for Content Topics

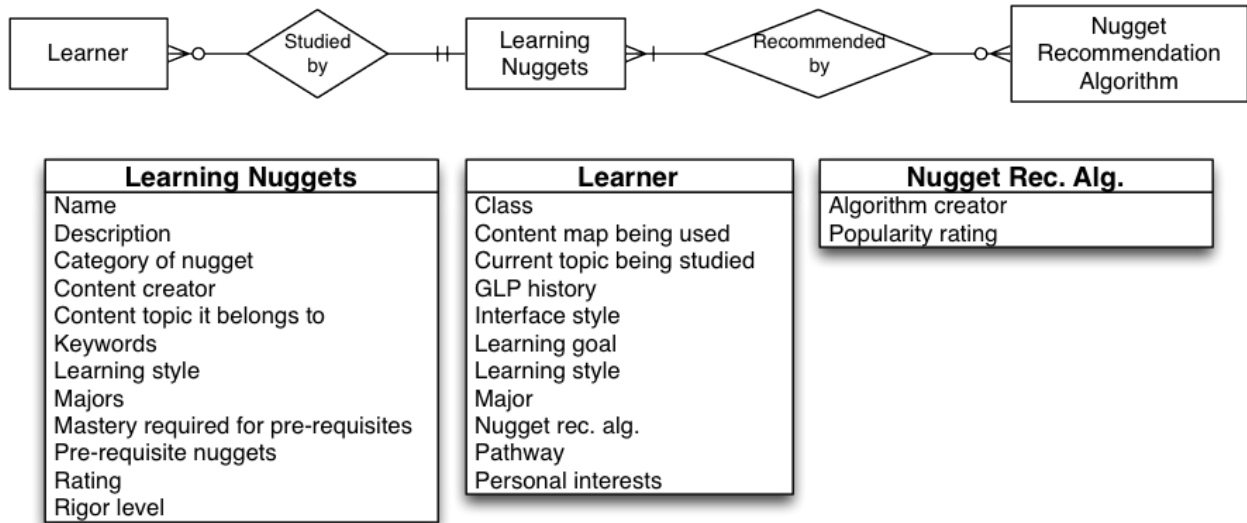


Figure 11. Conceptual Data Model for Learning Nuggets

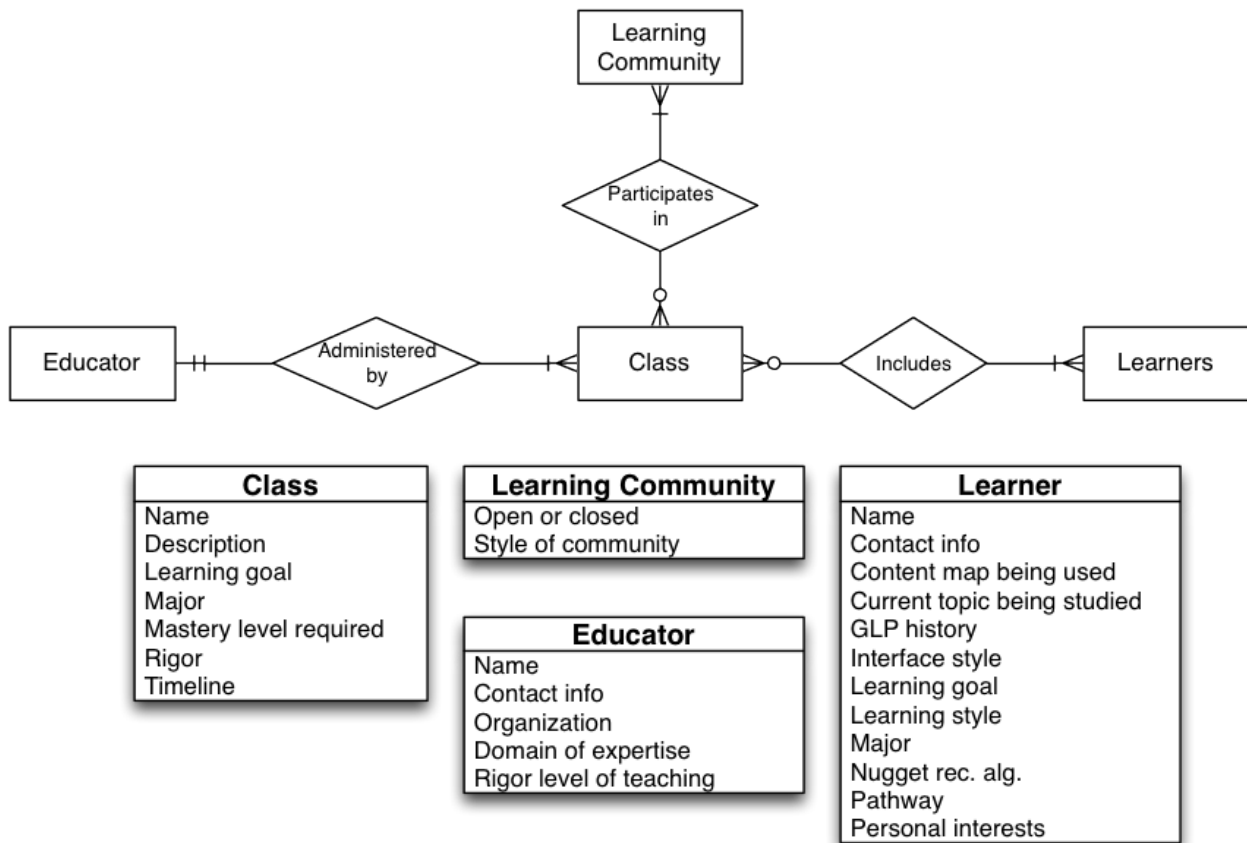


Figure 12. Conceptual Data Model for Educators

Swim Lane Process Flow Models

Swim lane process flow models provide a “behind-the-scenes” view of how different stakeholders and applications interact over time. Each model examines a specific action or process. As described in (Quigley, 2009), they consist of “actors” on the left-hand side, with time running horizontally. For GLP, actors are either users (i.e. learners), services, or applications. Each column contains the actions that an actor(s) take during that process step. The lines connecting actions represent communication between actors—at a minimum, process flow is handed off, but information could also be directly transferred.

These connections between actions help identify service calls and dispatcher publish-subscribe relationships. For example, connections to and from the data repository indicate a service call, and connections between applications indicate a dispatcher-controlled handoff. In the models we present here, time-periods are wrapped around the page due to space constraints.

Figure 13 shows a learner registration process. You can see that seven entities are involved in this process. Even though some are called only once, like the Pathways Assessment, they are included in the diagram for completeness and clarity. This process includes the learner selecting her first topic to study. Future interactions with her content map and pathway would be similar to the process in Figure 13, except without the initial profile and registration steps. Note that the dispatcher that handles the process flow between applications is not shown.

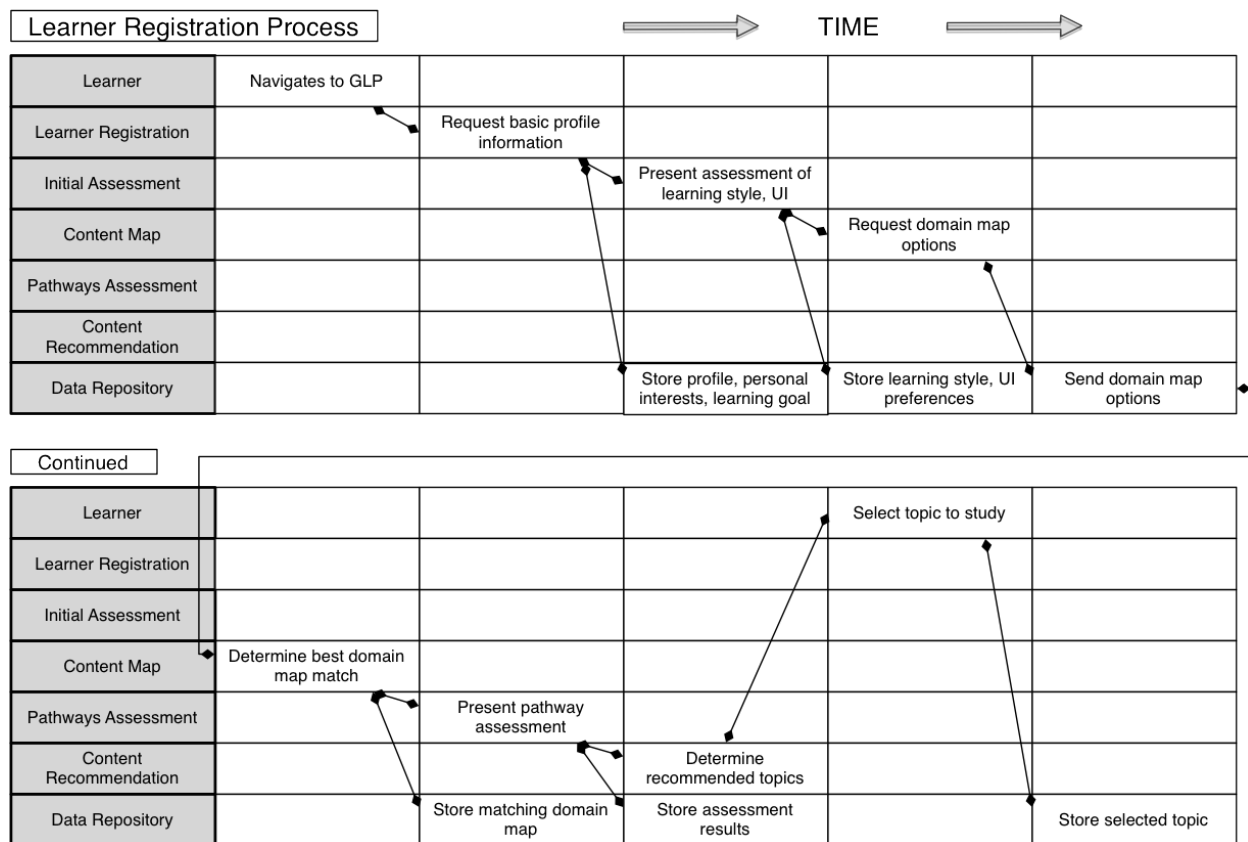


Figure 13. Swim Lane Model for Learner Registration

Here we include three additional process flow diagrams that cover important features for learners, content creators, and educators. In Figure 14, we show how a learner is recommended nuggets, selects one to study, practices some homework problems, and then takes an assessment. Her next steps depend on if she passes or fails the assessment. In Figure 15, we describe how content creators upload new nuggets, which then go through a quality review process. Finally, in Figure 16, we show how educators can create and manage classrooms of learners.

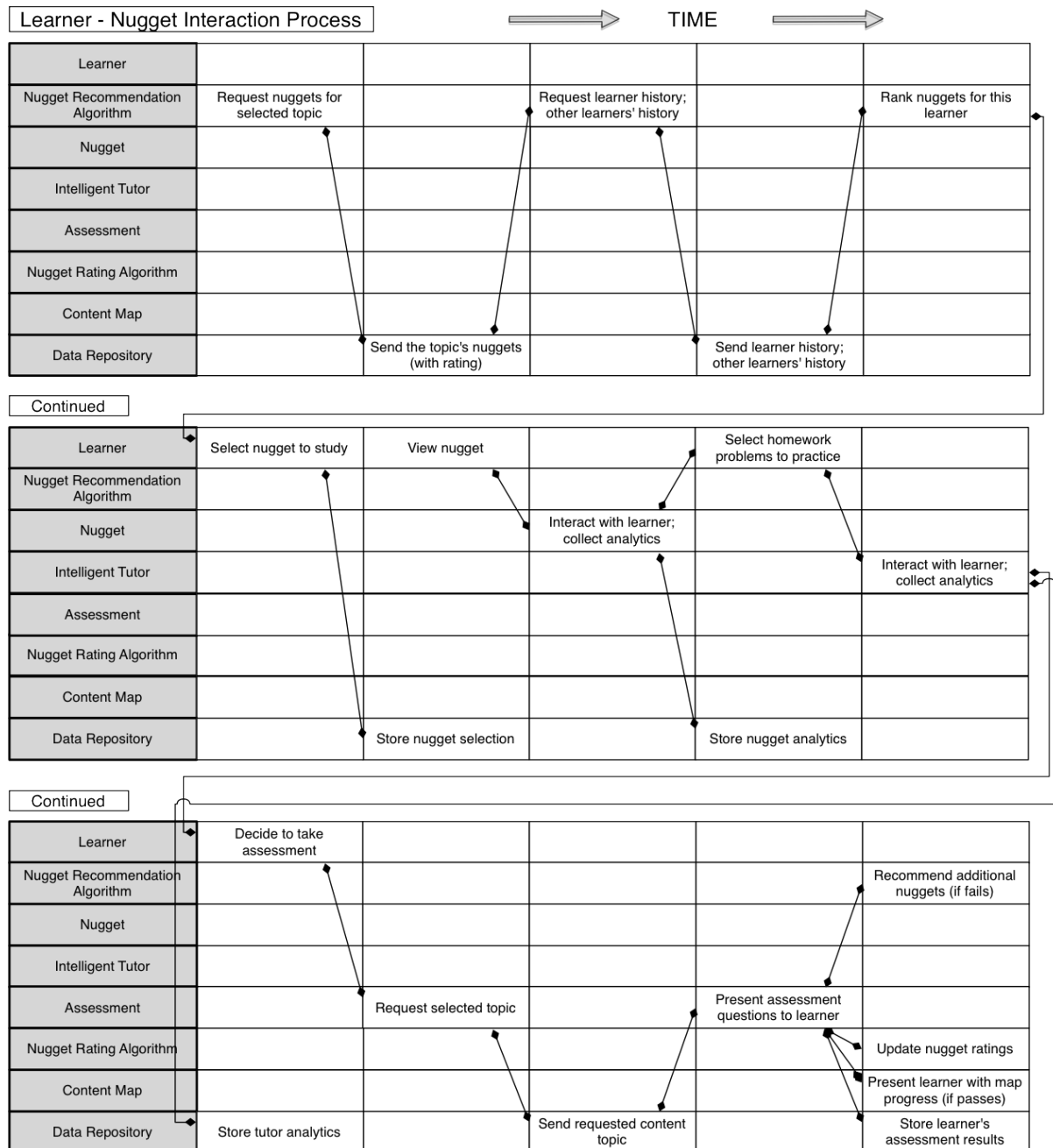


Figure 14. Swim Lane Model for Learner – Nugget Interactions

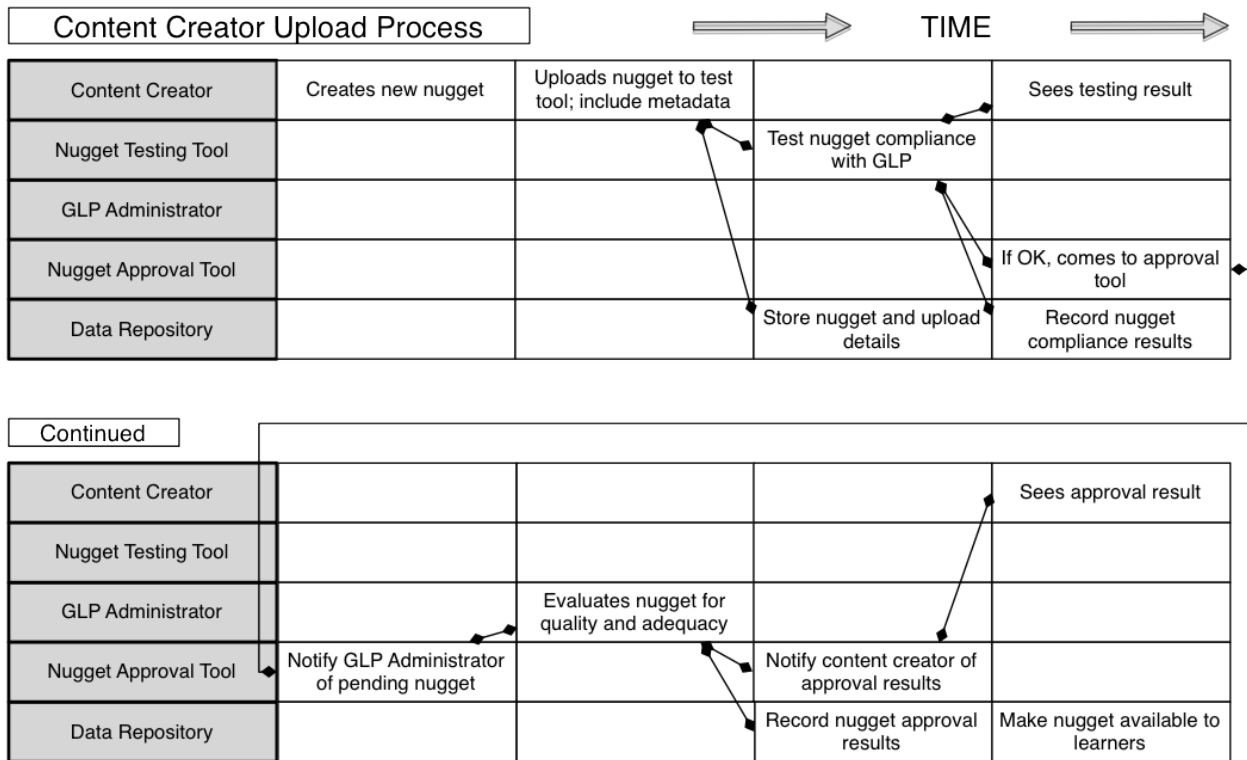


Figure 15. Swim Lane Model for Content Creation

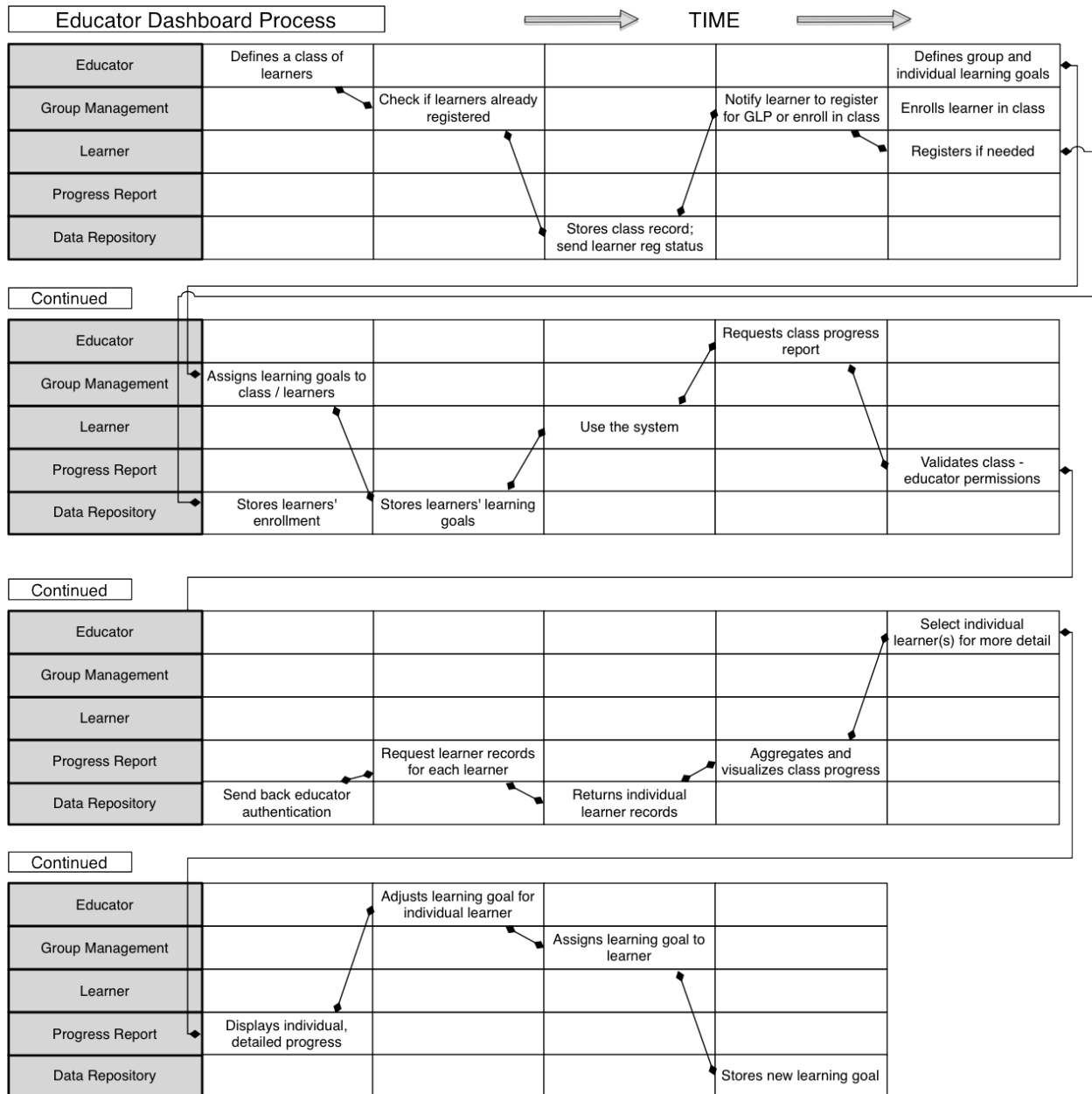


Figure 16. Swim Lane Model for Educators

Service Groups

From the swim lane process flow models, we derive two pieces of information: service calls to store or request information from the data repository, and application-to-application communication calls. We will discuss the service calls in this section and the app-to-app dispatcher communication in the next section.

Typically, service calls occur when a service wants to interact with the data repository. For example, the learner registration app would use a service call to store a learner's learning goal.

However, in order to reduce code repetition and improve maintainability, services are typically layered, which means that code for an action is stored in a single service, and services call other services to execute that action. For example, since an educator can also set a learner's learning goal as part of a class, it would be unwieldy to have both the learner registration and group management services manipulate the same "learning goal" field in the data repository. Instead, we consolidate the set-learning-goal service under the "learner management" service, which both the registration and group management services call when they need to change the learner's learning goal.

Adequately defining service groups and calls requires a significant investment in time and human capital. Fortunately, the heavy work has been done for enterprise-level platforms in education, like GLP. MIT's Open Knowledge Initiative (OKI), with support from the Andrew Mellon Foundation, has defined services for education. These have been adopted by various universities and companies in their products (Business Wire, 2002; Baving, Cook, & Green, 2003; Ternier, et al., 2006). Collectively called the Open Service Interface Definitions (OSIDs), these service groups are available online (OSID, n.d.). Compliance with the OSIDs ensures that services are cleanly separated and enables GLP's vision of easy upgradeability, maintainability, and application flexibility. Therefore, we build upon OKI's work and define GLP's service groups in terms of the OSIDs. When needed, we extend the OSID definitions to meet GLP's needs.

The rest of this section is organized by service group. In general, one service group supports an application type—applications with linkages to the data repository need service calls to support their activities. Each subsection then describes the OSIDs that provide the necessary GLP functionality for the given app. We also note which apps or services call the described service.

Four OSIDs will be used by all services, so we describe them here. These are the authentication, authorization, repository, and acknowledgement OSIDs. Only authenticated users can access GLP, and every service will need to verify this before responding to a user. Similarly, services must check that a user is authorized to perform a desired action—learners should not be able to delete nuggets, for example, only GLP administrators can. Since all services interact with the data repository, they will all utilize the repository OSID. However, this may need to be extended to also include storing of analytics information within the repository, in addition to assets, tags, and compilations. Finally, to encourage more community participation, all content and apps will be attributed to their creators through the acknowledgement OSID.

Assessment Service

The OSID assessment package offers services for creating, accessing, and taking assessments, and it is suitable for handling GLP's assessment needs. In addition, this OSID allows tracking of learner progress, test bank items used, and creation of new assessment items.

This service could be called by the assessment app.

Content Maps Service

Two OSID packages contain the functionality required for GLP content maps. These are the learning objectives and topology OSIDs. GLP will also use the graph feature of the topology OSID.

The learning objective OSID maps directly to the GLP idea of a content topic. Assets from the data repository can be assigned as activities to each objective—these equate to GLP nuggets and would use the nugget service to manage each individual learning activity.

The topology OSID with its graph component matches the pathways concept described in Section 2. It links together nodes, or learning objectives. As in GLP, different topologies can link learning objectives in different orders, and objectives can be added to topologies dynamically. Topologies can then be stacked or merged to create graphs, i.e. a content map.

However, two extensions to the routing and traversal methods in the topology OSID need to be constructed for GLP. First, all prerequisite learning objectives need to be included in the routing search results, not just the most direct, point-to-point route. In this way, learners see their entire pathways. For example, if a learner wants to study A-B-C, but B has pre-requisites A, D, E, the learner should see their “pathway” as including all nodes, A, B, C, D, and E, not just the “shortest” route of A-B-C.

Second, pre-requisite relationships need to be enforced during traversal. This should occur at both the application level as well as at the service level. This means a learner cannot traverse to a learning objective without mastering its pre-requisites.

This service could be called by the content map app or the content recommendation service.

Content Recommendation Service

The content recommendation service does not need to use a dedicated OSID. Instead, it performs its data requests and updates through the learner (user) management and content map services. Through the learner management service, the content recommendation service requests the learner metadata, current state of knowledge, and historical performance, as well as stores the topic selected to study. Through the content map service, the content recommendation service requests data on the learner’s pathway and its associated learning objectives.

This service could be called by the content map service.

Group Management Service

The group management service maps to the course OSID as well as relies on the learner (user) management service. The course OSID allows educators to create “courses” out of learning objectives. They can then enroll learners, define final assessment requirements, or even link together other pre-requisite courses or learning objectives. By using the learner management service, the group management service can also set individual learners’ learning goals.

This service could be called by an educator through a class management app or the progress report app.

Intelligent Tutor Service

No single OSID needs to be dedicated to the intelligent tutors. Instead, a combination of three other services will be used by this one: learner (user) management, nugget management, and assessment. Through the learner management service, the tutor service will be able to record learner proficiency and weaknesses, as well as request learner metadata. The nugget service allows the tutor service to find the right source material for targeted hints and explanations. Question banks and results are handled through the assessment service.

This service could be called by a tutor app or the assessment service, if a topic-level assessment needs to use a tutor.

Learning Communities Service

The forum OSID provides one means of supporting the learning communities service. It allows forum posts and replies, and may need to be extended to track user interactions. Additional types of learning communities may need other OSIDs that will need to be defined.

This service could be called by a learning communities app.

Nugget Approval Service

A unique OSID does not apply to the nugget approval service. This service can take advantage of the authorization OSID to check which users are authorized to review and approve nuggets (i.e. GLP administrators).

This service is called by a nugget upload app.

Nugget Recommendation Service

The nugget recommendation service will use two other services to achieve its functionality instead of a dedicated OSID. It will use the learner (user) management service to gather learner metadata, and the nugget service to gather nugget metadata. All this is used as input into the recommendation algorithms.

This service is called by the nugget recommendation app.

Nugget Service

Nugget services, like user management services, form a foundational service for many of the other GLP services. Only the learning objective OSID is needed to support the nugget service, so that nuggets (i.e. activities) can be linked to learning objectives.

For nuggets, the general repository OSID needs to be extended to include nugget metadata that GLP will use—such as relevant majors, keywords, rating, and learning styles.

This service is called by the nugget app, nugget recommendation service, intelligent tutor service, and nugget approval service.

Progress Report Service

A unique OSID does not apply to the progress report service. It will take advantage of three existing services: the group management service, the learner (user) management service, and the content map service. The group and learner management services will allow the progress report service to query for class and learner progress. This service can also query the content map service to check on pathways and progress towards achieving the assigned learning goal.

This service is called by an educator dashboard app.

User Management Service

Three OSIDs will be used for the user management service. The personnel, profile, and contact OSIDs allow GLP to maintain adequate information on each individual user. Each sub-type of users will have their own management services within this overall service, i.e. learners will have learner subservices, educators will have educator subservices, etc.

Different categories of users will also have different items stored in their profiles. For example, learner profile items will include attributes like preferred learning style, learning objective(s), and learner history. Dynamic, “smart” profile items can be used to manage learner attributes that will

constantly be updated by GLP, such as the current content topic being studied and learner history. All other profile items should also be updateable by the learner or the platform (like the learner's major, preferred learning style, personal interests), though it should be expected that these attributes be updated at a low frequency.

This service will be used by many other services and apps, such as the content recommendation service, group management service, intelligent tutor service, nugget recommendation service, progress report service, and user registration app.

Event-driven Model at the Application Layer

In this section we focus on application-to-application communication, or app process flow. As mentioned before, this process flow should be managed by a dispatcher or controller application that knows what category of app should follow which other apps. Part of this responsibility also includes delivering the learner's preferred type of app, for a given category. For example, while the dispatcher knows that a nugget recommendation app should follow the selection of a content topic on the map, it also needs to know which version of the recommendation app to call for a particular learner—the MIT version, the Stanford version, etc.

One way for the dispatcher to manage this flow is to use a publish and subscribe model. It can listen for applications to publish a message that essentially says "I am done!" The dispatcher then looks for application types that subscribe to the published message—multiple types of apps could subscribe to the same message, if multiple steps follow an action. For example, in Figure 14, after the final assessment, three steps are taken: 1) learner results are stored; 2) nugget ratings are updated; and 3) learner is passed to either the content map or the nugget recommendation app, depending on assessment results. Thus the assessment app publishes a message that three other apps subscribe to.

A list of publish and subscribe messages is provided in Table 13.

Application	Publishes	Subscribes to
Assessment	Assessment_passed Assessment_failed Assessment_completed	Take_initial_assessment Take_topic_assessment
Content Map	Take_initial_assessment Recommend_topics	Display_map Assessment_passed
Content Recommendation Algorithm	Topic_selected Recommend_nuggets	Recommend_topics
Intelligent Tutors	Recommend_nuggets	Initialize_tutor
Learning Communities	Display_map	Enter_community
Learning Nuggets	Recommend_nuggets	Nugget_selected
Learner Registration	Display_map	New_learner
Nugget Recommendation Algorithm	Nugget_selected	Recommend_nuggets Assessment_failed
Nugget Rating Algorithm		Assessment_completed

Table 13. Publish and Subscribe Messages

Once the dispatcher determines the types of applications that subscribe to the published message, it needs to query the data repository for what “flavor” of application the learner prefers. Since different developers will be able to create apps, learners can select the type of app that they prefer to use, i.e. an MIT app versus a Stanford app. Knowing the specific app, the dispatcher can then direct the learner to the right step in the process.

When implemented correctly, the application level interactions should appear seamless to all users. Users should not be able to distinguish that they are being passed to different applications, nor should they be able to detect that different versions of an app are being used.

Conclusion

This section presented a detailed system architecture for GLP. This architecture is cleanly separated into two layers—an application layer and a service layer. By providing this separation, GLP can achieve its goals of flexibility at the application layer, easier upgradeability, and maintainability. Third-party application developers will be able to find creative uses for GLP services and integrate them through new applications.

The architecture details are provided through conceptual data models, process flow models, service group definitions, and publish-subscribe relationships. The conceptual data models demonstrate the general structure of the data repository, and the process flow diagrams explain how applications will communicate with the data repository as well as each other. The service group definitions show how OKI’s Open Service Interface Definitions can adequately support GLP’s apps and overall architecture. Finally, the publish-subscribe model controls process flow at the application layer.

4. Social Impact

Introduction

Significant social issues and challenges exist around the topic of education; here, we broadly look at two categories of issues where GLP could have an impact—issues at higher education institutions, and post-graduation issues. Higher education includes college and university level education that leads to an accredited degree. What students decide to study and pursue at this level of education impacts the broader economy as they enter the workforce. In this section, we analyze GLP and how it may affect social issues in both of these categories. We will also discuss challenges in arriving at the potential impacts. Note that while it is impossible to accurately predict GLP's future impact, MOOCs' recent experiences give us hints of what is possible to achieve, and we will refer to them occasionally.

First, we will look at how GLP could affect three challenges in higher education: 1) lowering the cost of higher education, 2) improving accessibility to education in the U.S. and around the world, and 3) reducing STEM (Science, Technology, Engineering, and Math) diversion. The recent emergence of MOOCs is particularly interesting to analyze for these impact areas, as they have brought many of these questions into public debate. Achieving impacts in these areas depends on widespread acceptance of competency-based learning, increased Internet penetration, and institutional adoption.

Secondly, we will analyze three GLP effects on the broader economy: 1) impact of reduced STEM diversion, 2) improved lifelong learning, and 3) international impacts. Within higher education, a reduction of the STEM diversion rate will improve the economic performance of both STEM and non-STEM industries. Furthermore, the importance of a quality education does not only apply to the formal education system, but also for lifelong learners. Accordingly, a better-educated population could lead to improved economic development in certain countries, as happened with the "Four Asian Tigers" (Hong Kong, Singapore, South Korea, and Taiwan). International migration and cultural exchange could also be impacted. Achieving these impacts depends heavily on the general economy and government policies.

It is interesting to note that many of the social challenges listed above are the same issues that faced education over a decade ago (Larson & Strehle, 2001). Despite the progress made, these challenges and opportunities have only become more acute. Tuition costs continue to increase astronomically, the Internet has become faster and reaches more people, and yet education remains a very labor-intensive industry. Perhaps with the current interest and investments in technology-enabled education, dramatic and sustainable change can finally occur.

GLP and Higher Education

While all levels of formal education have received increased scrutiny around the world, the emergence of MOOCs has brought higher education to the forefront of the discussion. In the U.S., the cost of higher education in the last 30 years has risen 440%—ten times more than inflation, and even more than healthcare (Uebersax, 2009; Will, 2012). Globally, a growing youth population wants access to more educational opportunities, despite the rising costs. And an increasing awareness of the importance of STEM graduates and industries for economic growth (Kochan, 2012) has put attention on STEM diversion in higher education—especially for underrepresented minority groups.

Cost of Higher Education

As noted before, the cost of higher education in the United States has increased significantly in the last 30 years. In this time period, “the cost of a college degree has increased ‘12-fold” (Huffington Post, 2012). To pay for higher education, students and families have turned to public and private loans—currently, over \$1 trillion in outstanding student loans exists (CFPB, 2012). This seems unsustainable, and some propose that digital and online tools like GLP could help lower the costs associated with higher education.

Issue

Increased costs in higher education stem from a multitude of inter-related factors, which include the increasing competition for faculty, students, and research grants and the decreasing amount of state financial support (for public institutions).

Competing universities have created an academic arms race. To attract the best students and increase the universities’ prestige (and hopefully win more research grants), colleges and universities have built new research facilities, student amenities, and attracted star research faculty (Nocera, 2012). All of this spending requires universities to find new revenue sources, including alumni donations and student tuition and fees. Perversely, universities receive a double benefit from increasing tuition and fees—not only do they receive the revenue, but they also improve their rankings in magazines, improving their overall prestige (Nocera, 2012).

In addition to increased operating expenses to support the arms race, the steady reduction in state support for education has forced public schools to improve efficiency, raise tuitions, and better manage their resources (Rampell, 2012; University of California, 2011). In the University of California system, student tuition and fees cover 49% of their campus operating costs, whereas in 1990-1991, tuition and fees covered just 12% (on the flip side, state support has dropped from 78% in 1990-1991 to 39% today) (University of California, 2011). This just indicates how much of the financial burden of a college education has shifted to students and families.

Potential Impact

GLP could help achieve significant cost savings for both higher education institutions and individual learners. Institutions may be able to save faculty time and reduce overall administrative costs by using GLP for gateway courses, where thousands of students enroll every year. These savings could be passed on to students, reducing their tuition costs. Non-traditional learners could even use GLP directly to gain the same knowledge but for free.

Higher education institutions could cut their costs by decreasing the amount of time their faculty spend on instructional planning and reducing administrative overhead by using content and pathways from GLP, much like some universities are starting to do with MOOCs. San Jose State University (SJSU) offers one example. It is using MOOC courses in blended format for some gateway classes, and it has seen positive results in learning gains and retention—with the cost savings passed on to the students, who only pay \$150 for the course (Hepler, 2013; Harris, 2013). GLP could be used in similar fashion to significantly reduce costs for gateway courses at other universities.

Students could also see cost savings by using GLP directly. Non-traditional learners may be able to craft an entire course of study through GLP, using the experience as a basis for enrolling in other educational programs or for seeking employment. Others, who attend traditional

institutions, might opt to rely on GLP outside of any institutional environment—effectively supplementing their educations. If their home institution accepts “GLP credit”, they could even apply their knowledge towards a traditional academic program.

Challenges and Limitations

While GLP could significantly lower the cost of higher education, it faces two main barriers in achieving this. First, society, employers, and government need to accept a competency-based mindset for education instead of today’s “seat-time” mindset. Second, a significant up-front development cost could deter creation of GLP.

For GLP to achieve widespread adoption, people and employers need to be able to translate achievement in GLP into terms that are generally accepted—for example, “course credit.” Since GLP is topic-based, its form of mastery represents competency-based learning, which in current education, has been pioneered by Western Governors’ University (WGU) (Western Governors University, n.d.). WGU’s model has gained acceptance among its students and employers of its alumni, though it has not spread as fast as proponents had hoped for. Nonetheless, it shows that competency-based education can work, and with the right social message, GLP could achieve the same success.

Similarly, traditional institutions would need to accept Internet-based learning and mastery as equivalent to their residential courses. While this has not yet occurred on a large scale, some institutions do accept transfer credit from accredited online programs, and even MOOC courses have been recommended for transfer credit (Lederman, 2013). Ironically, Lederman notes that even the institutions that created the recommended MOOC courses will not accept transfer credit for them, though the path may be paved for GLP (Lederman, 2013).

Another challenge is the significant up-front development cost required to create and deploy GLP. While it is impossible to estimate this cost, MOOCs may serve as good reference points. These costs can then be broken down into platform development and content creation costs, both of which are labor-intensive endeavors.

Software development of GLP would rely on a dedicated team of software developers. One large MOOC provider has a core staff of 40 employees, with 17 full-time developers (Coursera, n.d.). By performing a quick calculation using the average, entry-level developer salary for the region and considering administrative overhead, a conservative estimate would be that their annual development cost is over \$3 million dollars (Salary.com, n.d.; Hadizma, 2005). Since GLP would be a more sophisticated platform, it would require at least a comparable development team and cost.

Content will also be expensive to create. The initial content modules will most likely need to be created by the GLP team to demonstrate the platform’s potential and attract more contributors—this will involve curriculum planning, content creation, and final editing. The University of Texas (UT) system, part of edX, allocated \$5 million to create four complete classes (Ura, 2012). Estimating that each UT class covers a 14-week semester (University of Texas, n.d.), this is equivalent to about a \$30,000 investment per one hour “lecture”—roughly equivalent to a nugget in GLP. One professor who created a MOOC course reports that he spent two weeks, full-time, to develop and create each lecture; many professors also put in additional effort during the course itself to interact with students (Kolowich, n.d.). Creating content for an entire GLP pathway would require at least a similar investment of resources.

However, it should be noted that these costs should go down with time. Once developed, content can be re-used, and the marginal cost per additional student is \$0. And as with any open-source, community project, as GLP gains adoption, people will be able to contribute their own material and software applications, lowering total costs.

Some claim that this lowering of educational costs could have negative ramifications, by forcing universities to lower tuition and fees, potentially driving second and third-tier universities out of business (Cusumano, 2013). While it remains to be seen if that comes to pass, it is not clear that this outcome would be negative for students, as long as the newer, alternative educational opportunities are of equal or higher quality than existing options. Broader economic impacts on employment in the education field, though, are certainly possible.

Accessibility of Education

Traditional education institutions have not been able to keep pace with the demand for quality education. This is true not just in higher education, but also at primary and secondary school levels. Youth at all levels of schooling need access to a high quality education to insure their future contributions to society.

Issue

This global demand for quality education arises from a combination of demographics and social belief. Globally, the number of youth who want and need education is increasing. At basic levels of schooling, developing countries and rural areas face a great challenge—few students make it through primary and secondary schools. In the OECD, about 20% of students drop out before graduating from high school, and one can only assume that the percentage is worse in less developed countries (OECD, 2012). These students, especially those from disadvantaged backgrounds, face inequity in the educational system, limiting their motivation and engagement in school.

However, for the students who do graduate from secondary education and reach the higher education system, there is not enough capacity to serve them. California's university system already turns away an increasing number of applicants (Keller, 2011). Growing populations in other countries face similar challenges—one estimate is that 40 million Indian youth will need a college education by 2020 (Thrift, 2013).

All of these youth want and need better educational opportunities because a better education leads to better wages and a better life in the long-term (Barrow & Rouse, 2005). Employers are more frequently using university degrees as criteria for even the most entry-level positions, because the degrees signal other, intangible skills and motivations—putting pressure on students to graduate (Rampell, 2013). More and more students will thus need ways to gain not just a basic education, but also a university degree.

Potential Impact

GLP would allow anyone with an Internet connection to access its high quality content. The meteoric rise of MOOCs and the Khan Academy demonstrate that reaching a wide audience of individual learners is possible. Thousands of K-12 schools also have integrated a blended component into their pedagogical models, showing that widespread institutional adoption of new pedagogy can also be achieved (Staker, Chan, Clayton, Hernandez, Horn, & Mackey, 2011). Widespread usage of GLP would mean that all people, regardless of background, could improve their knowledge and future opportunities.

One specific example of this potential impact is for youth in rural areas. Whereas it may be inefficient or economically unreasonable to build schools and deploy teachers to rural communities with small populations, youth in those areas will be able to tie into a global learning community using an Internet connection. Through GLP, they can learn from high quality material that would be impossible to distribute to them otherwise; one can even imagine that rural youth educate themselves all the way through an entire university curriculum. The Hole-in-the-Wall project in India has shown that a simple computer kiosk in a village leads to amazing self-directed learning results among disadvantaged youth (Dangwal & Thounaojam, 2011); with GLP, these learning gains could be even more pronounced.

Similarly, disadvantaged females could benefit from a learning solution like GLP. Like the youth mentioned before, women living in shelters also saw learning gains with the Hole-in-the-Wall project (Dangwal & Sharma, 2013), which shows that a solution like GLP could have a broad social impact. Females face unique educational challenges in many regions, since they may be culturally unable to travel to and from school without a male escort, there may be a lack of female role models in education, they have monthly menstrual cycles that may keep them at home, and there may be a cultural emphasis on male education over female education. By offering a high quality stay-at-home option, GLP will enable females to receive the education they deserve, under culturally acceptable conditions.

Challenges and Limitations

To achieve these benefits, GLP will need to piggyback on other technologies, such as mobile and fixed Internet access. A promising sign is that broadband penetration is increasing globally. In 2012, over one billion people accessed the Internet through a 4 Mbps or faster connection—13% more than the previous year (Akamai, 2012, Q4). These speeds would allow learners to access videos and other nuggets within GLP. However, GLP's reach is limited by broadband penetration.

Even with Internet access, some learners may have to deal with government blocking of GLP or its components. For example, 215 students in Pakistan could not access course videos for a MOOC after the government blocked access to a video-sharing website in September of 2012 (Ripley, 2012). Fellow classmates scrambled to find a workaround solution so their Pakistani peers could finish the course. Similar situations could limit GLP's impact in certain countries or regions, and unfortunately they are outside of GLP's direct control.

For youth who are not receiving even a basic education, GLP may be hard pressed to assist them without a broader social investment. As noted by Chimombo (Chimombo, 2005), those youth not actively participating in basic education typically have external reasons why they are unable to participate—such as a need to support their families or poor local infrastructure. Simply offering GLP on the Internet will not be sufficient to reach these groups; broader social and public assistance will be needed so that these youth can receive a high quality education. However, GLP could be used as a tool to help lower the total cost of this public assistance.

STEM Diversion

Compared to other fields, a significantly higher percentage of students who enter university interested in STEM switch to another major—a phenomenon known as STEM diversion. Many studies have examined this phenomenon, since STEM industries are critical to economic growth and STEM diversion depletes the human capital required for these industries.

Issue

One study found that approximately 44% of entering students who express an interest in a STEM major switch to a non-STEM major during their undergraduate years; women tended to switch more than men (Seymour & Hewitt, 1997). Looking at current data, approximately 1 million students declare into a STEM major as freshmen, and about half switch out of STEM majors by graduation (Robelen, 2013).

Students typically offer a variety of reasons for switching out of STEM majors, including financial constraints and needing to graduate earlier, better job prospects in other fields, and originally feeling pressure to major in STEM (Seymour & Hewitt, 1997; Kolko, 2013). Since financial considerations have already been discussed in the Cost of Higher Education section, here we focus on academic issues in STEM.

Seymour and Hewitt found that switchers and non-switchers jointly shared many concerns about their general STEM educations (Seymour & Hewitt, 1997). A subset of these concerns are listed in Table 14. Note that SME refers to Science, Mathematics, and Engineering—what we now call STEM.

STEM Education Concerns
Lack or loss of interest in science
Poor teaching by SME faculty
Feeling overwhelmed by the pace and load of curriculum demands
Inadequate high school preparation in terms of disciplinary content or depth, conceptual grasp, or study skills
Conceptual difficulties with one or more SME subjects

Table 14. Subset of STEM Education Concerns

However, since the weaknesses in STEM education do not only affect those who change majors, these concerns do not only affect diversion. Seymour and Hewitt find that among upperclassmen that stayed in a STEM major, their poor education in the gateway courses left them with “a shaky theoretical foundation for higher level work. They described uncertainty about particular bodies of material, and described gaps in understanding which they had not been able to close” (Seymour & Hewitt, 1997). Thus, improving learning in gateway courses is not only important for STEM persistence, but also for improving STEM mastery for those who stay in STEM majors.

Underrepresented Minority Groups in STEM

The National Academy of Sciences (NAS) notes that STEM diversion is particularly acute for underrepresented minorities, who enter university with comparable levels of STEM interest as their white and Asian peers, but who have much lower persistence and completion rates (National Research Council, 2011). This has a negative effect on younger generations. The lack of STEM role models who are underrepresented minorities will discourage future generations from entering those fields. Furthermore, since employment prospects are growing significantly faster in STEM fields compared to non-STEM fields, this lack of diversity could eventually lead to a sharp, self-reinforcing socio-economic divide based on ethnicity.

Potential Impact

GLP could help improve STEM retention from three aspects. First, it can better prepare high school students for the transition to college. Second, it can support differentiated instruction in the classroom, which has shown to improve learning outcomes (Subban, 2006). Finally, it can personalize learning to better engage learners.

Before students arrive on a college campus, some are already poorly prepared due to lack of good high school preparation. GLP could address specific knowledge gaps for each student during pre-freshmen usage. This kind of personalized preparation has been recognized to be important for boosting graduation of engineering majors, and is being tested at Texas A&M University (Texas A&M University, n.d.).

Once students arrive on campus, differentiated instruction via GLP might address the issues with poor STEM faculty teaching. In gateway courses with hundreds of students, it is hard to cater to each student's needs. However, GLP enables differentiation by providing to each student the content that they need, using a learning process and learning materials suited for them.

Personalized learning on and off-campus is another way to increase STEM interest and overcome conceptual difficulties; using both academic and non-academic interests to adjust teaching has proven successful in increasing STEM retention and improving learning gains. Lord presents several universities that now tailor introductory math courses for engineering majors, which has led to improved retention and graduation rates (Lord, 2012). Walkington found that matching learning materials to students' out-of-school interests helped some students perform better with an interactive, computer-based algebra tutor (Walkington, 2013).

In addition to these three specific benefits, GLP may be able to decrease STEM diversion by simply freeing up educator time for more two-way interaction with students. Recent evidence from San Jose State University shows that online course materials coupled with educator-led discussions significantly improved passing rates in a gateway engineering course from 60 percent to 90 percent—this could lead to more students graduating with STEM degrees (Friedman, 2013).

Underrepresented Minority Groups in STEM

GLP could be one tool that helps keep underrepresented minority students in STEM fields. The NAS recommends 5 academic and social support initiatives to improve STEM persistence in this group (National Research Council, 2011): summer programs, research experiences, professional development, academic support and social integration, and mentoring. GLP could directly help institutions with at least two of these—summer programs and academic support and social integration. Note that GLP could be used in this fashion to enhance learning for any student, not just those in minority groups.

As discussed earlier with Texas A&M University's personalized pre-calculus program, GLP could act as a bridge between high school and college. Universities could enroll incoming minority students in GLP to target their individual learning needs and get them prepared for the university's curriculum.

In terms of academic support and social integration, the NAS provides examples of these activities, such as peer-to-peer support, study groups, social activities, tutoring, and mentoring (National Research Council, 2011). GLP helps with all of these things. Universities could utilize GLP's learning communities to bring together their minority students and thus encourage collaborative learning and mentoring.

Challenges and Limitations

All of the benefits outlined above are predicated on institutional adoption of GLP. As we have seen with MOOCs, not all institutions will be interested in using GLP as part of their curricula—adoption does require a different approach to education, and institutional change can be difficult. However, to reach its full potential, GLP needs a large number of learners using the platform—thus an effort should be made to recruit educators and institutions. This may involve gathering broad stakeholder support early on, updating the platform for individual university needs, and offering enhanced class management and student tracking tools.

GLP and the General Economy

Through its impacts on higher education, GLP could subsequently influence the general economy. By reducing STEM diversion, GLP helps improve economic competitiveness in both STEM and non-STEM industries. GLP also opens up doors to lifelong learning, which is seen as increasingly important in the knowledge economy. Furthermore, GLP could lead to diverse international impacts in the field of education.

STEM Diversion and the Economy

STEM graduates and their skills are valued in both STEM and non-STEM fields. The skills they gain from their STEM training include technical, core skills (like mathematics and science), as well as more transferable but difficult to measure skills (like critical thinking and active learning). Two recent reports note that STEM graduates are regularly drawn into non-STEM careers, such as business, medicine, or law (Carnevale, Smith, & Melton, 2011; Ruark & Graham, 2011), and the U.S. Department of Commerce reports that approximately “two-thirds of the 9.3 million workers with a STEM undergraduate degree work in a non-STEM job” (Langdon, McKittrick, Beede, Khan, & Doms, 2011). Thus increasing the number of STEM-trained college graduates will have a broader social benefit in terms of jobs and the economy.

Issue

Globally, companies claim that it is increasingly hard to find qualified employees due to lack of both technical and employability skills (Manpower Group, 2012). This will only get more severe in the future as competition for employees grows—in the U.S., STEM jobs are expected to grow 17% by 2018 and non-STEM jobs by 9.8% (Langdon, McKittrick, Beede, Khan, & Doms, 2011).

Yet high youth unemployment also exists around the world (International Labour Office, 2012). If STEM training offers a way for students to gain these desired technical and employability skills, then encouraging students to persist in STEM majors should lead to a higher quantity of qualified candidates.

Potential Impact

GLP could have a significant, long-term impact on the lives of students who currently divert from STEM—half a million students a year, in the U.S. (Robelen, 2013). One piece of evidence that demonstrates the lifelong value of a STEM degree comes from the National Science Foundation (NSF), which reports that science and engineering bachelor’s degree holders, regardless of actual occupation, have higher annual incomes over their lifetimes compared to non-STEM bachelor’s degree holders; they also experience lower and less volatile unemployment (National Science Board, 2012). Larson also promotes the idea that STEM competencies are valuable life-skills, even to those not employed in STEM careers (Larson, n.d.).

The National Academy of Sciences (NAS) also seems to support the linkage between STEM skills and career and life success. Carnevale et al.'s STEM skills fall within the Cognitive Domain of the 21st Century competencies, as defined by the NAS in their report *Education for Life and Work* (Pellegrino, et al., 2012; Carnevale, Smith, & Melton, 2011). After a thorough literature review, the NAS authoring committee concluded that these cognitive competencies, which include critical thinking, information literacy, reasoning and argumentation, and innovation, have consistently shown “positive correlations (of modest size) with desirable educational, career, and health outcomes” (Pellegrino, et al., 2012). Thus GLP could improve hundreds of thousands of lives around the world.

Challenges and Limitations

GLP's challenge in achieving this impact is that it only has partial influence on the outcome—much relies on the entire STEM curriculum of a university, of which GLP is only a small part. If STEM curricula continue to adequately address employer needs, as Carnevale and his colleagues propose, then GLP could have this broader economic impact by retaining students in STEM programs. However, it appears that universities could be doing a better job in this regard.

A persistent challenge between educational institutions and industry has been how well higher education prepares students for the labor market. 72% of education providers think their graduates are prepared for entry-level employment—but only 42% of employers believe their new hires were adequately trained (McKinsey Center for Government, n.d.). Thus a matching definition and measurement of “employable skills” is not shared between educational institutions and industry and could slow down the achievement of these impacts.

Lifelong Learning

Traditional students are not the only ones who could benefit from additional learning opportunities. Lifelong learners who want to pick up or demonstrate new skills could also contribute to industry needs for skilled labor. Alternatively, they could also seek learning opportunities for personal fulfillment. In either situation, we can see from MOOC user demographics that lifelong learners are an important constituency for GLP (Kolowich, 2012; Balch, 2013).

Issue

Lifelong learners are a critical component of today's knowledge economy, but they have a lack of formal learning opportunities (OECD, 2004). As noted by the OECD, lifelong learning benefits the individual, an enterprise, and society in general, yet opportunities are limited for older adults and those in early childhood (OECD, 2004).

An additional challenge is equal accessibility to lifelong learning opportunities that do exist. By inadvertently slanting them towards adults with higher educations, such learning inequalities perpetuate and can lead to greater social division (OECD, 2004; Schuller & Watson, 2009).

Potential Impact

Field notes that concrete research on the benefits of lifelong learning are only starting to emerge (Field, 2012). On the whole, a small, positive impact is seen in both economic and non-economic benefits.

One could imagine that GLP enhances the lifelong learning impact that we currently see, by improving accessibility and lowering costs, compared to the “campus-based” learning opportunities that are commonly researched. More lifelong learners from disadvantaged backgrounds could improve their knowledge levels at home or in community centers, as well as

join a supportive, online learning community.

Challenges and Limitations

The impact of GLP on lifelong learners will heavily depend on Internet penetration, technical literacy, and adoption. The first two factors are especially important to consider for disadvantaged learners who may not have home Internet access or the basic technical knowledge required to use GLP. More general, social-wide support to encourage adoption among that population may be required.

Employer acceptance of GLP as a certification would only influence adoption by the subset of lifelong learners who seek new job opportunities. However, those who are looking to change jobs may face the same social and employer acceptance challenge that we mentioned in the Cost of Higher Education section.

International Impacts

In addition to GLP's impact on job skills and the labor market, it could have broader international impacts. These are difficult to describe in detail, since they are influenced by many factors. However, some examples we will discuss briefly are long-term economic growth, higher education partnerships, and cultural influence of education.

Issue

Every country is looking for ways to stimulate economic growth, and education is often seen as a key component of doing this successfully. The “Four Asian Tigers” (Hong Kong, Singapore, South Korea, and Taiwan) are often held up as successful examples, even though they each had different educational policies (Morris, 1996). However, one challenge that all such countries face is brain drain—the well educated are also those with the best opportunities to emigrate.

One way that countries have tried to reduce brain drain is by building high quality, local educational institutions—typically in partnership with a more prestigious, international university. Faculty, pedagogy, research, and even students are often shared in such arrangements. Yet building an entirely new university is a capital-intensive task. For example, the Singapore University of Technology and Design (SUTD) is a new university collaborating with MIT (not a branch campus, like some partnerships). The Singaporean government is building SUTD a completely new campus, with capital costs of over \$200 million USD in 2012 (SUTD, 2012). Approximately 75% has gone to land leasing, while the other 25% of expenses cover building and facility construction, equipment, and other capital property—and the campus will not be completed until 2015, so costs should rise.

The spread of such “Western” education symbolizes what some pejoratively call “cultural imperialism”—disseminating cultural values and norms through education (Carnoy, 1974). Nonetheless, international education has a generally recognized positive impact on students' personal growth and cultural awareness; unfortunately, minorities tend to participate less frequently than others (Salisbury, Umbach, Paulsen, & Pascarella, 2009). However, with the power of the Internet, many regions and universities now have a chance to project their own unique cultural values and norms around the world and open up opportunities to more students for cross-cultural educational experiences.

Potential Impact

Based on the human capital theory, the general economic benefits of a better educated population due to GLP should be positive (Sweetland, 1996). GLP could even provide greater benefits by slowing down brain drain. Countries could build low-cost, high-quality local

educational experiences around GLP that attract and retain their best and brightest youth—who traditionally would have studied in another country. These local experiences would also save countries money compared to creating brand new universities; the money saved could be used to address other factors that lead to brain drain, such as living conditions and pay.

Given that many countries face high youth unemployment (International Labour Office, 2012), adding to the number of youth in developing countries by slowing brain drain may not seem like a great policy. However, there exists a potential upside. The youth who emigrate and study abroad are generally the most motivated, intellectually curious, and entrepreneurial. If some stay in their home countries and are given appropriate support, they may apply their efforts to creating businesses and job opportunities for other youth. Given that 25% of U.S. startups have a foreign-born co-founder (Wadhwa, 2009), they could certainly start companies in their home countries if given the opportunity.

As an open platform, GLP will encourage the sharing of cultures and values among all of its users. For nearly five years, MIT BLOSSOMS has demonstrated the cross-cultural reach of Internet-based educational materials—partners from seven countries have created interactive, high-school STEM videos in four languages (BLOSSOMS, n.d.). We can also see this happening with MOOCs. The initial content has been predominantly created by U.S. educators, but this is changing. Universities in the U.K. have started their own MOOC platform, with its own local content (Futurelearn, n.d.), and Chinese educators have already released their own courses (Sharma, 2013). This shows that many countries and regions have valuable cultural and educational content to share with others, which could be supported by GLP. This could also help bring cultural understanding to students who traditionally do not study abroad, such as minority groups.

Challenges and Limitations

Many factors could influence these potential impacts, and the challenges are many. In general, the impacts are only observable in the long-term and can be subtle or difficult to measure. Thus one of the main challenges is finding a business model to support the long-term sustainability of GLP. Only through long-term use of the platform could we see some of these impacts emerge.

Summary of GLP Social Impact

If successfully implemented, GLP could have significant impact on broader society. Many challenges exist, such as building up significant user communities, finding a sustainable business model, and significant up-front development costs. However, once past those challenges, GLP could lead to changes in higher education and the general economy.

In higher education, GLP could have three impacts. First, it could dramatically change the cost equation for students and institutions. Second, it could improve accessibility to a quality education for many students and disadvantaged populations around the world, especially as broadband infrastructure improves. Finally, GLP could reduce the STEM diversion rate, especially for underrepresented minorities.

Reducing the STEM diversion rate helps GLP with its broader economic impact. These broader impacts also occur as GLP offers high quality lifelong learning opportunities. A country or region that commits to widespread use of GLP could thus see improved economic development by improving its human capital. GLP could also have some long-term international impacts in terms of brain drain, university partnerships, and cross-cultural understanding.

5. Conclusions

This report presented a system architecture and social impact analysis for a personalized learning platform called Guided Learning Pathways (GLP). GLP radically improves the concept of education by catering to learners' interests and engaging them through personalization. While it would have significant up-front development costs, the marginal costs for each additional student are nominal and the potential impact is significant.

Section 2 of this report showed how GLP provides an educational experience different than current educational models. It does this through a comprehensive learner scenario and application descriptions. We described eight apps that represented eight GLP functionalities, with each description also outlining specific benefits and features.

Section 3 discusses a software architecture that supports the GLP features mentioned in Section 2. This two-layer architecture allows for easy upgradeability, maintainability, and flexibility by drawing clear boundaries between applications and services. In addition to an overall architecture diagram, we provided three pieces of information to describe the architecture: conceptual data models, process flow diagrams, and service group definitions. We also described how different applications will communicate with each other.

In the final section, we discussed the social impacts of GLP and what challenges it faces in achieving these impacts. Specifically, we explored social impacts on higher education institutions and the broader, international economy. For higher education, GLP could reduce costs, increase accessibility, and reduce STEM diversion. These impacts could lead to strengthening of the broader economy, improving options for lifelong learning, and result in general international impacts regarding brain drain and cultural understanding.

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Appendices

Appendix A

This appendix provides mathematical and programmatic notations for the GLP applications as well as examples of each parameter. Each section builds upon the related app in Section 2, but uses formal notation to supplement the reports’s verbal descriptions. In our notation, L refers to learners, T to content topics, and N to learning nuggets.

This appendix may be of use for developers and practitioners who wish to implement a portion of GLP. For these readers, pseudocode is provided for the content and nugget recommendation algorithms.

Learners

The main report provides a verbal description of learners and their attributes. These are collectively referred to as $L^{PARAMETERS}$, defined in Table 15.

Attribute	Notation	Definition	Example Data
General Interests	$L^{INTERESTS}$	“Real World” interests that help engage the learner inside of GLP and can be used to match nuggets to learners.	Basketball, Celtics, rap music
GLP History	$L_t^{HISTORY}$	Learner’s history of GLP usage, over time. Includes nuggets used, when they were used, and assessment results.	Nugget 5 / November 1, 2012 5:15pm Assessment / Derivatives / Passed / 95% / November 6, 2012 10:12am
Learning Goal	L^{GOAL}	An optional attribute, this helps further define a learner’s goal in using GLP. This could be a single topic, a group of topics, or a pre-defined pathway.	Derivatives Derivatives, Limits, and Integrals “Introductory Biology Calculus”
Major Field of Study	L^{MAJOR}	Learners enter GLP with different fields of study. This attribute helps to define what types of topics and nuggets might be interesting and engaging for the learner.	Biology
Preferred Interface	$L^{INTERFACE}$	A learner’s preferred methods of interacting with a computer.	Node-based
Previous Knowledge Level	$L_t^{MASTERED}$	Learners enter the GLP system with prior knowledge, which affects what they need to learn. This updates over time to reflect new knowledge that is mastered (in GLP or outside of GLP).	Random numbers, limits, functions
Preferred Learning Style	L^{STYLE}	A learner may prefer certain types of learning materials to others.	Visual

Table 15. Learner Attributes

Content Maps

Content topics have different attributes associated with them. In a deployed GLP, this information will need to be encoded as metadata. One method of doing this in an object-oriented programming framework would be to define Content topics as a class with the following data fields, collectively referred to as $T^{PARAMETERS}$ and seen in Table 16.

Field	Notation	Description	Data Field	Example Data
Name	T^{NAME}	The name of the topic.	Text	Derivatives
Description	T^{DESC}	A description of what the topic means.	Text	The derivative of a function is its instantaneous rate of change.
Keywords / Tags	T^{TAGS}	Additional information that might be useful in classifying this topic.	Array	[introductory, sinusoids, calculus]
Level of Rigor	T^{RIGOR}	The level of difficulty of the topic.	Text	Undergraduate
Major(s)	T^{MAJORS}	Major fields of study that this topic relates to.	Array of Strings	[Biology, Engineering, Economics, Physics]
Mastery Level for Pre-requisite(s)	$T^{PREREQ_MASTERY}$	Mastery required for pre-requisites before attempting this topic. Different majors may have different requirements.	Array of Floats	[0.95]
Pre-requisite Topic(s)	$T^{PREREQS}$	Topics that need to be mastered prior to this one. Different majors may have different pre-requisites.	Array of Strings	[Function]

Table 16. Encoding Example for Content Topics

Pathways

To determine which pathway a learner should follow, GLP will look at the following learner attributes (and Table 17) and search for a pre-defined pathway according to their values:

Learner Attribute	Notation
Learning Goal	L^{GOAL}
Major Field of Study	L^{MAJOR}

Table 17. Learner Attributes That Define Her Pathway

Given all of the topics in the content map, denoted by the set T , the pathway of topics required for the learner to achieve her learning goal will consist of a subset of T , which we call $T_L^{PATH_{TOTAL}}$.

$$T_L^{PATH_{TOTAL}} = \{ \forall T_i \in T | \{ (L^{MAJOR} \in T_i^{MAJORS}) \wedge ([L^{GOAL} = T_i^{NAME}] \vee [(L^{GOAL} = T_k^{NAME}, k \neq i) \Rightarrow (T_i^{NAME} \in T_k^{PREREQS})]) \} \vee \{ \exists T_j \in T_L^{PATH_{TOTAL}}, j \neq i | T_i^{NAME} \in T_j^{PREREQS} \} \}$$

$T_L^{PATH_{TOTAL}}$ is thus unique to each learner, L , and constant until she changes her learning goal or major. As we can tell from the equation above, GLP calculates $T_L^{PATH_{TOTAL}}$ from the set of topics that match the learner's major and either matches her goal explicitly or is a pre-requisite for her goal. Furthermore, GLP performs a breadth-first search to include all other topics that are pre-requisites for any topic in the current $T_L^{PATH_{TOTAL}}$, until all "fundamental" topics are included.

GLP can compare $T_L^{PATH_{TOTAL}}$ to the set of topics in the learner's previous knowledge at time t ($L_t^{MASTERED}$) and flag her mastered topics. At any time t , if the learner has mastered topics in the set $T_L^{PATH_{TOTAL}}$, GLP marks them as "completed"—thus the uncompleted pathway at time t is $T_{L,t}^{PATH} = T_L^{PATH_{TOTAL}} \setminus L_t^{MASTERED}$. Given prior research into learning sequences, a learner might have a different sequence of topics within $T_{L,t}^{PATH}$ to reach Newton's Method compared to others (Fischer, Rose, & Rose, 2006). Thus as GLP evaluates her individual performance, it can offer the learner different pathways to achieve her goal.

Content Topic Recommendation Algorithms

The pathways section described the algorithm to determine the topics in a learner's pathway at any given time t . Once a learner's $T_{L,t}^{PATH}$ set of topics has been determined, the topic recommendation algorithm generates a subset of un-mastered topics where the learner has mastered all pre-requisites, $T_{L,t}^{OPTIONS}$, where $T_{L,t}^{OPTIONS} = \{ \forall T_i \in T_{L,t}^{PATH} | T_i^{PREREQS} \subset L_t^{MASTERED} \}$. The learner can also follow her self-interest and choose to study topics not in the set of $T_{L,t}^{OPTIONS}$ and where she has mastered the pre-requisites for her selected topic. In our notation, $T_{L,t}^{SELECTED}$ represents the learner's selected topic at time t .

Pseudocode

Path = Array

For all Topics:

 If (Topic == Learner.goal) OR

 (Topic is in the Pre-requisite chain of Learner.goal) THEN

 (NOTE) Pre-requisite chain is defined as all of the pre-requisites of a node until you reach a node with no pre-requisites (i.e. the pre-requisite of the pre-requisite of the pre-requisite, etc.)

 Add Topic to the Path array

 Add the Topic's pre-requisite chain to the Path array

Options = Array

For all Topics in Path

 If (Topic is NOT in the Learner's list of mastered Topics) AND

 (Learner has mastered all of Topic.pre-requisites) THEN

 Add Topic to Options array

Present options array to learner for them to pick a topic to study.

Learning Nuggets

Learning nuggets have different attributes associated with them. In a deployed GLP, this information will need to be encoded as metadata. One method of doing this in an object-oriented programming framework would be to define learning nuggets as a class and define the following data fields, collectively referred to as $N^{PARAMETERS}$ and seen in Table 18.

Field	Notation	Description	Data Field	Example Data
Name	N^{NAME}	The name of the nugget.	Text	Calculus: Derivatives 2
Description	N^{DESC}	A description of the nugget.	Text	Using the derivative to find the slope at any point along $f(x)=x^2$
Category	$N^{CATEGORY}$	This is the type of nugget.	Text	Lecture Notes
Content Topic	N^{TOPIC}	The content topic that the nugget belongs to.	Text	Derivatives
File Location	N^{FILE}	URL or server location for the actual nugget.	Text	http://www.khanacademy.org/math/calculus/differential-calculus/v/calculus--derivatives-2
Keywords / Tags	N^{TAGS}	Additional information to classify this topic.	Array	[slope, curve, tangent line]
Learning Style	N^{STYLE}	The learning style of the nugget.	Text	Visual
Level of Rigor	N^{RIGOR}	Level of difficulty. From 0 (easy) to 10 (hard).	Integer	5
Major(s)	N^{MAJORS}	Major fields of study that this nugget relates to.	Array of Strings	[Biology, Engineering, Economics, Physics]
Nugget Creator	$N^{CREATOR}$	The content creator who uploaded the nugget.	Text	Khan Academy
Pre-requisite Nugget(s)	$N^{PREREQS}$	Some nuggets may be part of a sequence. If so, this field defines pre-requisite nuggets.	Array of Strings	[Calculus: Derivatives 1]
Rating	N_t^{RATING}	The effectiveness [0, 10]. Might differ for different categories of learners. Updates over time.	Float	8.57

Table 18. Encoding Example for Learning Nuggets

GLP combines the nugget attributes with learner attributes to create personalized rankings of each nugget. The most highly recommended nuggets are those that GLP believes can best help the learner master a specific content topic. A mathematical representation of this is shown in the following section.

Nugget Recommendation Algorithms

In order to find the best nuggets for each learner GLP can use a regression analysis to estimate the rank of each nugget. To determine the nugget's fitness for a specific learner, GLP uses the efficacy of the same (or similar) nuggets on the assessment performance of other learners with similar interests and characteristics. To this end, the recommendation algorithm takes a specific learner's attributes, nugget attributes, and other learners' historical performance, then scores the nuggets using regression analysis. This leads to a function, $f(\)$, that analyzes all nuggets.

First, the nuggets must be filtered according to the learner's selected Topic: $N_{L,t}^{OPTIONS} = \{N_i \in N \mid N_i^{TOPIC} = T_{L,t}^{SELECTED}\}$. The nuggets are then given a score according to the input parameters listed above and presented to the learner in decreasing order of score. This score is unique to each learner and varies over time, t , and according to other learners' experiences:

$$N_{L,t}^{SCORE} = \{\forall N_j \in N_{L,t}^{OPTIONS}, \forall L_k \neq L \mid f(N_{j,t}^{PARAMETERS}, L_t^{PARAMETERS}, L_{k,t}^{HISTORY})\}$$

One simple recommendation algorithm would perform a linear combination of the learner's major field of study, the learner's preferred learning style, and the rating of the nugget. It ranks all nuggets in decreasing order of *score*, according to the following equation:

$$N_{L,t}^{SCORE} = w_{major} * match_{major} + w_{style} * match_{style} + w_{rating} * N_t^{RATING}$$

When the learner's major matches the majors covered by the nugget, $match_{major} = 1$ ($(L^{MAJOR} \in N^{MAJORS}) \Rightarrow (match_{major} = 1)$). Similarly, when the learner's preferred learning style matches the style of the nugget, $match_{style} = 1$ ($(L^{STYLE} = N^{STYLE}) \Rightarrow (match_{style} = 1)$). N_t^{RATING} is the GLP-calculated rating for each nugget, as mentioned above. Each nugget's rating is a value from 0 to 10 that automatically increases when a learner passes an assessment test after using nugget N_j and decreases when a learner fails an assessment after using nugget N_j . Note that one weakness of this approach is that a learner can select multiple nuggets to study before taking an assessment—thus a “good” nugget can be unfairly punished by the other nuggets the learner uses before her assessment. However, this problem should be mitigated with a large number of learners. $w_{major} + w_{style} + w_{rating}$ will always sum to 1.

Pseudocode

Learner selects a Topic to study

For all Nuggets in that Topic:

Assign each Nugget a personalized score, based on:

Learning Style match with Learner

Major / field of study match with Learner

Other Learners' success using the Nugget (via a rating or direct search against Learner histories)

Rank order all Nuggets in descending order of score

Present Nugget Recommendation List to Learner

Learner chooses nugget(s) to study

Intelligent Tutors

The intelligent tutor modules will need to communicate with the other modules, such as the content recommendation algorithm and the nugget recommendation algorithm. To facilitate these messages, a possible encoding mechanism to report on learner progress and knowledge is presented. These could be referred to as $ITS^{PARAMETERS}$ and are seen in Table 19.

Field	Notation	Description	Data Field	Example Data
Name	ITS^{NAME}	The name of the intelligent tutoring system.	Text	Bayesian Knowledge Tracing
Expert Model	ITS^{EXPERT}	The mathematical model representing expert knowledge.	Depends	
Learner Model	$ITS^{LEARNER}$	The mathematical model representing individual learner knowledge.	Depends	
Pedagogy Model	ITS^{PED}	The pedagogy model that the ITS will use to bridge the gaps between the learner model and the expert model.	Depends	
Learner Weaknesses	ITS_L^{WEAK}	The topics for learner L, which she is weak in. Should update constantly as the learner interacts with the ITS.	Array	[slope, derivative, product rule]

Table 19. Encoding Example for Intelligent Tutoring Systems.

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