An Asynchronous, Personalized Learning Platform – Guided Learning Pathways

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Abstract

The authors propose that personalized learning can be brought to traditional and non-traditional learners through an asynchronous learning platform that recommends to individual learners the learning materials best suited for him or her. Such a platform would allow global learners to advance towards individual learning goals at their own pace, with learning materials catered to each learner's interests and motivations. This especially proves useful to learners in developing countries who may not have access to traditional learning opportunities. This paper describes the authors' vision and design for a modular, personalized learning platform called Guided Learning Pathways (GLP), and its characteristics and features. We provide detailed descriptions of and propose frameworks for critical applications like the Content Map, Learning Nuggets, and Recommendation Algorithms. A threaded user scenario is provided for each application to help the reader visualize different aspects of GLP.

Keywords— online learning, asynchronous learning, personalized learning, learning styles, pathways, content map, instructional technology, recommendation algorithm

INTRODUCTION

Education is experiencing many shifts; Clayton Christensen says that it is being "disrupted" by online learning [**1**]. The Khan Academy [**2**] has enabled widespread blended learning, and prestigious universities like Stanford, Harvard, and MIT have adopted online education through MOOCs (Massive Open Online Courses).

However, many of these platforms still utilize the industrial model of education with a "pre-defined course," where all students must try to learn the same topics at the same pace during a set time period. Many students drop out—they may have the ability to learn the material, but struggle with the time constraints [**3**]. Others, especially those in developing countries, may not have the educational background or regular access to technology to succeed in current MOOC courses [**4**]. Nonetheless, global broadband access on both fixed and mobile devices is growing, with 75% of current mobile subscriptions in developing countries and overall mobile access growing at about 60% a year, showing that more learners will have access in the future [**5**]. However, as people in developing countries gain access to quality educational materials online, we need to ensure that the materials are appropriate for their backgrounds. Personalized learning platforms that let people learn on their own schedules, with materials suited to their individual needs can address this issue in all countries.

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 [**6**]. More recent research in traditional classrooms has also shown the benefits of letting students learn at their own pace and focus on topics that interest them [**7**] [**8**].

Recommendation algorithms to support flexible and personalized learning have been explored by many, such as [**9**] [**10**] [**11**] [**12**] [**13**] [**14**] [**15**]. These studies have shown promising results at both the course level as well as for individual learning activities. Their systems cater to the needs of individual learners, allowing them to learn topics based on their interests and backgrounds.

However, a large-scale solution that reaches millions of students has not yet appeared. Researchers and startup companies have begun exploring adaptive technologies to support personalized learning in classrooms, although a comprehensive solution for non-traditional learners has not yet appeared (see [**16**] [**17**] [**18**] [**19**] [**20**]). Siemens, et al., propose perhaps the most comprehensive such platform, which they call Open Learning Analytics [**18**]. While the concept is similar to GLP in terms of use of analytics to improve individualized content delivery, their platform focuses on organizational and institutional use, and limits learners to traditional "classes" instead of topic-based learning. Furthermore, by incorporating concept maps, GLP allows both traditional and non-traditional learners to take an assessment test and place themselves into the appropriate learning location on their concept maps.

The European community has developed a large-scale solution for personalized learning, called ROLE (Responsive Open Learning Environments), which does cater to non-traditional learners [**21**]. 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 assist learners by creating widgets that help teach specific concepts, rather than directing learners towards certain topics. In turn, learners can "mash up" different resources to create individualized learning experiences. GLP falls somewhere in between ROLE and Open Learning Analytics when looking at educator and learner roles—it provides a learner-centered environment, but with guidance from educators and domain experts.

While GLP would require significant up front investment to create adequate content and the base platform, 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 [**22**]. Over time, researchers and companies would be able to design new and improved applications (apps) that interact with the platform through standard communication interfaces.

This paper presents an overview of the Guided Learning Pathways system with additional detail on the apps that would interact with the core platform. A threaded example that continues through each app provides details on how the third-party apps could interact with an example learner.

OVERVIEW OF GLP

Many recent publications and companies put forth ideas for personalized education platforms in classrooms [**16**] [**20**] [**23**]. However, these platforms require the use of a teacher or in-person facilitator to guide the students or to teach the content—this limits their reach and impact. As an alternative, GLP provides a large-scale, asynchronous platform where domain experts can encode their guidance, which could then be accessed by large numbers of learners, including non-traditional learners. Non-traditional learners include lifelong learners or those from low-resource regions.

GLP is a modular platform, and as new learning technologies emerge, new apps could integrate in. Different learners could select which type of app they wish to utilize—one may wish to use a crowdsourced *content map*, while another may wish to use a custom version created by a high-school teacher in the U.S. (Figure 1).

Insert Figure 1 here.

Figure 2 lists some GLP terminology, with more detailed definitions in later sections.

Insert Figure 2 here.

As learners make their way through individual pathways, each has a personalized experience. GLP will access data repositories of learning nuggets, like MIT's Core Concept Catalog [**24**] and recommend to each learner the nuggets most suitable for her. GLP determines suitability based on each learner's learning style preferences, personal interests, and other learners' success with each nugget; however, learners will be free to choose the resources they use. Even though it has not been proven that there exists a single, unique learning style per individual [**25**], learners may define a preference but select what seems more engaging for them at any given moment. As more learners use the system and GLP gathers better data on nuggets, GLP can discard poorer performing nuggets.

Analyzing learner history and performance, GLP can also match learners into learning communities, which can help learners master content [**26**]. These communities could consist not only of other learners (as in the OpenStudy model, see [**27**]), but also live human tutors who interact synchronously with the learners in individual tutoring sessions.

As shown in Figure 1, the GLP platform will be modularized, and different organizations or individuals can plug-in their apps. Envisioned apps could include (but are not limited to): 1) content map, 2) data repository, 3) intelligent tutors, 4) learning communities, 5) learning nuggets, 6) recommendation algorithms, and 7) user interfaces. Several of these will be described in more detail later. This document presents a fluid and evolving description of GLP, and the examples described within represent possible implementations—readers should not interpret them as being the only implementations.

LEARNERS

Description

We begin by defining GLP learners. As mentioned in the overview section, we envision that both traditional and non-traditional learners will use the GLP platform. Traditional learners are those in age-appropriate learning environments with access to a qualified teacher, while non-traditional learners may include lifelong learners with specific learning needs, youth in rural areas, or people in developing countries. By giving non-traditional learners opportunities to learn from high-quality material appropriate for their knowledge levels, GLP differs from current MOOC trends (which offer high-quality materials at a standard difficulty level, which may not be appropriate for many learners).

Each learner embodies a set of inherent attributes that GLP uses to improve her learning and better engage her. Some of these may include her non-academic interests—for example, if she is a Boston Celtics fan, she may be recommended more basketball related nuggets. Similarly, her explicit educational learning goals (i.e. introductory biology math) and interests (computational biology) help GLP focus the types of material and topics presented to her.

A learner may also have learning preferences that change over time. Parameters like her preferred learning style (i.e. visual, textual, or auditory) or even her preferred interface style (i.e. node-based, virtual world) could be adapted to better engage the learner and improve her learning.

Determining Learner Attributes

Some learner attributes can be determined by GLP upon registration, either through a questionnaire or assessment test. As GLP gathers more information from a large number of learners and learns more about each individual's learning patterns, its recommendations should improve. 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. More detail on this is provided in the Nugget Recommendation Algorithms section. Figure 3 summarizes key learner attributes.

Insert Figure 3 here.

Threaded Example

María Lopez García wants to study ecology, but she needs to work full-time to support her family. Thus, after finishing high school, she took a job as an administrative assistant at a local clinic. She just finished her first year of work, but wants to improve her education and open up future career opportunities in forestry. Her friend José tells her about this online program that can help María refresh her high school biology and help her learn what she needs for a career in a natural protected area.

After María gets home from work, she finds the Guided Learning Pathways website and registers. She is presented with several different learning materials talking about trees. One is a visual resource that 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 María which material she preferred, and she selects the visual category. GLP records this and will use that information as her initial learning style preference—GLP will initially recommend more visual nuggets to her, but it may adjust the recommendations as it learns more about her learning habits.

María also has a chance to list some of 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 Facebook interests, which include salsa music, football, and food.

User Interface

Description

The user interface allows each learner to navigate her pathway through a visualization method that is more intuitive for her (*pathways* are described in the Content Map section). One can imagine that these interfaces are further personalized with overlays—for example, John and María might both prefer **geographic** interfaces, but John likes baseball and María likes football, so John's content topics are mapped to baseball stadiums while María's are mapped to football stadiums. Even if John and María interact during the same activity, they each see different views. Current data visualization tools allow users to see data in different forms; with GLP, learners would be able to interact with the same core set of data and learning materials, but through completely personalized interfaces. A simple example is the skins that people use to customize software like Gmail or Winamp.

Threaded Example

After importing her Facebook interests, María then has a chance to pick an interface style. GLP offers some pre-defined categories, including node-based (Figure 5), geographic-based (Figure 4), and 3D virtual world. Since María enjoys geography, she selects the geographic option. GLP knows that she has an interest in football, so it uses a football overlay. GLP starts her off with a trip around the world. and asks her to visit all the countries' national stadiums that participated in the 2010 World Cup, with a general East-to-West direction of travel. She sees the initial map from Figure 4, which shows different topics in biology calculus overlaid onto baseball stadium locations.

Earlier in the afternoon, María had chatted with a new friend in the class, Mark. Mark prefers simple interfaces, and he selected a node-based interface. María appreciates that she could select an interface that would be more dynamic and engaging for her.

Insert Figure 4 here.

Content Map

Description

After a learner registers, she is introduced to the GLP content map. The content map takes the traditional, high-level idea of a subject (like calculus) and breaks it down into topic-based maps. This idea has been explored in *learning trajectories* (used in youth math education) and ASSISTments [**28**] [**29**]. The GLP maps could initially be designed by domain experts and then refined over time with user data. Instead of every topic being linearly connected as in a course syllabus or textbook, topics would be connected to related topics, and such topic-strings could be learned in parallel. For example, learning *Fractions* does not depend on knowledge associated with *Exponents*, so the two concepts could be learned in parallel; on the other hand, *Addition and Subtraction* needs to be learned before *Multiplication and Division*, so these topics must be learned sequentially [**30**]. Thus, embedded within each topic is a list of pre-requisite topics that a learner must master beforehand.

When she registers, the learner takes an assessment test to determine her mastery level and placement on the content map. Given the pre-requisite relationships within GLP, it will be assumed that if a learner tests out of a topic, she will also have mastery of the pre-requisite topics. If it is later discovered that she is weak in a specific area, GLP can add topics to the learner's pathway and reinforce her knowledge. As the learner uses GLP, she can also test out of topics through an assessment test. The required mastery level for each topic will be discussed in the next section, and could differ among learners.

By focusing on topics instead of "classes," GLP enables more efficient learning of core topics across disciplines. For example, physics and calculus might share many of the same topics, and in a content map the shared topics could be merged to reduce redundancy and show concept relationships.

Content Map Customization

The content maps could also be customized for different majors and interests. Tailoring subjects like mathematics to engineering has been shown to improve student engagement and retention at several universities in the U.S.A. [**31**]. The National Research Council's (NRC) BIO2010 report also supports the idea of specialized math; the NRC outlines the specific mathematics requirements for an undergraduate biology curriculum [**32**]. Thus, in GLP, biology majors could each learn what is relevant for their interests, with examples and topics oriented towards their field. An extension of this idea would be that different majors might have different levels of mastery required for different topics. Biology majors might need to master *Derivatives* at only an application level, whereas engineers might need to master it at a synthesis level (in following Bloom's original Taxonomy [**33**]).

Learner-generated changes in the map could be driven by annotations, such as how Boston Children's Hospital's OpenPediatrics project allows users to annotate and comment on video lecture snippets [**34**]. As learners use nuggets and note areas of confusion or add resources to clarify a topic, other learners can comment on the usefulness of these resources. Topics can then be broken down to create a more detailed content map. At the university level, MIT Crosslinks provides one example of an expert-generated content map for calculus [**35**]. A portion of the Crosslinks data is shown in Figure 5.

Insert Figure 5 here.

Another way to modify the map could be through learners. Research has shown that infants learn reading through different pathways [**36**]. One can imagine that sequences of topics are chained together, but different learners might learn each sequence in a different order. However, this will need to be better defined through more research—GLP could enable this by including a framework to allow learners to try different sequences of topics.

Figure 6 summarizes the content topic attributes that each topic will need to have.

Insert Figure 6 here.

Topic Mastery

When examining a content map, links between content topics show a pre-requisite relationship. Mastery of all pre-requisites is required before studying follow-on topics, and the level of mastery required could differ per learner, as described in the section above—thus, learners must take an assessment test before they can move on from any given topic. Bloom's Taxonomy (and its revised version) offers ways for GLP to define these assessments [**33**] [**37**]. In their revised taxonomy, Anderson and Krathwohl offer action-oriented ways to measure student learning (pp 67-68) [**38**]:

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.*

Once a learner has demonstrated the appropriate level of mastery, defined by their individual needs and learning goals, they can move on to other topics in their pathway.

Pathways

As defined above, pathways are sub-sections of the content map that help achieve specific learning goals. These pathways could be pre-defined by domain experts or determined by aggregated learner history. For example, looking at Figure 5, one can see that a pathway to learn *Newton's Method* goes through *Function*, *Derivative*, and *Taylor Series*.

To determine which pathway a learner should follow, GLP uses a learner's learning goal and major field of study. This pathway could be crowdsourced from other GLP users and then tailored for each individual. One could imagine that some learners might need a refresher on polynomials, which would be an added step between *Taylor Series* and *Newton's Method*. A learner's overall pathway should include her explicit learning goal, if she picked a specific topic (i.e. *Derivatives*), or all of the topics related to her field of study (i.e. introductory biology calculus).

When a learner registers and a pathway is determined, GLP places her onto the appropriate starting point of her pathway. The exact location depends on each learner's previous knowledge mastery and assessment results.

Threaded Example

GLP analyzed María's learning goal of a biology and ecology career. It has determined that she needs to master a set of topics from the calculus content map—the blue and red arrows in Figure 8 represent two different *pathways* between topics within biology calculus that both allow her to achieve her learning goals. Figure 7 shows one possible topic mapping for the blue arrows, using data from MIT Crosslinks [**35**]. María can select the pathway that seems best suited for her, with some guidance from GLP. Based on the popularity rating of the blue pathway, she chooses to follow it first—if it does not seem to be working, she can always change later on.

Insert Figure 7 here.

Insert Figure 8 here.

María then gets a short assessment test to determine where on the blue pathway she should start. GLP finds that in some topics, María is actually at an intermediate level, while in others she is at a basic level. GLP records the topics that she already knows and places her at the start of the pathway—María needs to review some topics.

Content Recommendation Algorithms

Description

Guidance through content maps has been researched before. 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 icon [**39**]. GLP builds upon this by allowing different learners to have different content maps to suit their learning needs (as mentioned in the Pathways section, individuals learn things in different orders). Furthermore, GLP will allow personalization of the learning materials, exercises, and example.

Similarly, García et al., report on a tool that provides peer and student feedback and recommendations directly to teachers, to help them improve courses over time [**11**]. This tool allows teachers to share course materials and looks for trends in effective course components, i.e. was forum posting correlated with high or low test scores, was a specific unit correlated with better course performance, etc. GLP builds upon this content-level work by automating the feedback and improvement process, and then offering better pathway recommendations to individual learners. Instead of the course changes affecting all learners, only those who would perform better would see the change. For example, García et al., discuss a forum, which may be unhelpful for most students (low forum participation correlates to high scores). Under their scenario, a teacher may decide to remove the forum entirely. However, that forum may be beneficial to a subset of learners—GLP would be able to detect the difference in utility across learners and recommend the forum (or learning unit, etc.) on the pathway of a subset of learners but not others.

Thus, two "levels" of recommendation algorithms will be used by GLP: for the content topics and the nuggets. It can be imagined that different types of algorithms are tested at each level or adapted to individual learners and backgrounds, so that learners receive the most useful recommendations for them. Here we describe the content topic recommendation algorithms.

The content topic recommendation algorithm identifies the content topics that remain on the learner's pathway, which he or she has not yet mastered. GLP then recommends those topics where the learner has mastered all pre-requisites, or topics with no pre-requisites. The learner can also follow her self-interest and choose to study topics not on her formal pathway, but where she has also mastered the pre-requisites.

Threaded Example

Since María selected the blue Pathway, GLP calculates the topics where she showed sufficient mastery in all the pre-requisites. However, during her assessment test, María 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 María can start with.

GLP finds two topics along the blue pathway with no pre-requisites—*Functions* in Australia, and *Differential* in Ivory Coast. It presents both options to María. She still remembers some of the concepts in *Functions* from her high school class, so she decides to visit ANZ Stadium in Sydney.

Learning Nuggets

Description

Once a learner selects a topic, GLP uses statistical methods to infer about her learning preferences and skills in order to recommend the learning nuggets best suited for her (described in the Nugget Recommendation Algorithms section). These nuggets include lectures notes, media (video, audio, etc.), assignments, and assessment tools that are crowdsourced from public contributors as Open Educational Resources, much like Wikipedia. Nuggets will have an associated level of rigor to suit different learners and could range from elementary school to postgraduate level. Each nugget will also receive a dynamic rating that reflects its effectiveness in helping learners master its topic.

The learner studies as many nuggets as she wants, before choosing to take a topic assessment to test her mastery level. If she proves her mastery of the topic, she can move on and select another topic to study. If the learner has not mastered the topic, she will be presented with a re-ranked list of nuggets for the same topic.

To help match nuggets to learners, nuggets need to be tagged with metadata. Some of these have been mentioned above, such as rigor. Others might include learning style or non-academic themes; examples might be videos, lectures, or activities. This requires that GLP include an initial way to identify a learner's preferred learning style. Learning styles could be defined as visual, textual, or auditory—note that this means a video-based resource could be a visual, textual, or auditory learning style, depending on the characteristics of the video.

Nuggets will also be categorized into different types, each of which represents a different pedagogical tool. Some example categories are seen in Figure 9.

Insert Figure 9 here.

Over time, a learner's preferred learning style could be refined from her initial selection by analyzing each learner's behavior in GLP and which nuggets prove most effective in advancing the learner's mastery. While research has not definitively proven that learners have a **single** learning style that helps them learn most effectively [**25**], the idea of providing multiple options that can engage learners in different ways is an alternative solution, incorporated into the Universal Design for Learning (UDL) framework [**40**]. By providing different types of nuggets, GLP merges both approaches and provides the flexibility of UDL and learner choice while also providing a structure for learners who have a preferred learning modality the majority of the time. As Pashler et al. [**25**] mention, there exists anecdotal evidence about individual learners "getting" a topic using some specific learning style when a different style did not work for them before or did not work for other learners, so providing multiple options is essential (and limiting learners to a single style may not be a great idea).

As noted above, nuggets could be crowd-sourced from high-quality, existing OER or created specifically for GLP. A quality-review process will ensure that nuggets meet GLP's criteria for inclusion into the platform. Such crowdsourcing of content has proven successful in other Internet platforms, such as Wikipedia and open-source software like Linux.

GLP will constantly review and evaluate the nuggets after a learner uses them. 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 remove the nugget for that subset of learners or remove it completely from the data repository. Figure 10 summarizes learning nugget attributes.

Insert Figure 10 here.

GLP combines the nugget attributes listed in Figure 10 with learner attributes listed in Figure 3 to create personalized rankings of each nugget for each learner. The most highly recommended nuggets are those that GLP believes can best help the learner master a specific content topic. We provide more detail in the Nugget Recommendation Algorithms section. As third-party contributors create and add nuggets to GLP, learners get presented with more choices in "real-time", as shown in Figure 11.

Insert Figure 11 here.

Threaded Example

María selected to first visit the Socceroos and ANZ Stadium, where she will study *Functions*.

Entering the stadium, she sees that different sections contain different rigor levels and types of nuggets. The **Luxury Suites** are undergraduate interactive applets, the **Lower Section East – Midfield** seats are graduate lecture notes, and the **Upper Section North – Goal Area** seats are undergraduate case studies. It appears that there is one nugget assigned per seat, so she has a wide variety of options to choose from. As she wanders through the Lower Section East – Corner, 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. María stops at one seat, and she sees: "Creator: John Smith" "population growth" "video" "visual" "4.2".

NUGGET RECOMMENDATION ALGORITHMS

Description

As mentioned previously, many researchers have also investigated recommendation algorithms using collaborative filtering, preference-based, neighbor-interest-based, and other data mining techniques [**9**] [**10**] [**11**] [**12**] [**13**] [**14**] [**15**]. Nadolski et al. have used simulators to test personalized recommendation algorithms [**41**], and we have created a distinct simulation platform to compare nugget recommendation algorithms [**42**].

The nugget recommendation algorithm identifies and ranks the best nuggets for a learner that will help her master the topic in the most efficient way possible (i.e. in less time, most intuitively, with least frustration). Our method assumes that a large dataset of learning nuggets exists within GLP along with a large number of learners using the platform. There exist many ways to recommend nuggets under these conditions—one envisioned method would be to use the learner's preferred learning style (i.e. visual nuggets), personal interests (i.e. baseball), and historical data about each nugget or sequence of nuggets (i.e. 40% of learners with similar profiles who used nugget X mastered the topic, vs. 70% of learners with similar profiles who used nugget Y mastered the topic). Nugget efficacy can be measured in terms of marginal improvement for similar learners. To find this relationship among nugget efficacy, nugget attributes, and learner attributes, we can use different statistical tools such as regression, prediction models, clustering and classification, and understanding the learner's preferences.

After scoring all nuggets for the learner's selected 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 top of the list so that learners use them and help them develop a history. Similar to a search engine's results, this list of nuggets will differ between individual learners. From this list, the learner can study as many nuggets as desired (and in any order), and she can choose to follow or not follow the GLP recommendations. When she feels ready to test her knowledge, the learner can choose to take an assessment to measure her mastery level. If she reaches the required mastery level, the learner moves on and selects another topic to study. If the learner returns to the same topic, the nuggets will be re-scored using updated information from all learners, and the learner can select new nuggets to use.

Threaded Example

María stops her random exploration of ANZ Stadium 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 Lower Section West – Midfield, the Lower Section East – Corner, Upper Section North – Goal, and the Luxury 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.

María wanders over to the Lower Section West – Midfield to read some undergraduate lecture notes from MIT, then heads over to the Upper Section North – Goal to analyze an undergraduate level case study from Stanford. Finally, she plays with some undergraduate level interactive applets in the Luxury Suites made by *MarineBiologist123*, a practicing biologist. María loves exploring ANZ Stadium while learning more about *Functions*!

María feels like she has a good grasp of the concept of *Functions*, so she returns to the ticket office and asks for an assessment test. 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, and GLP records this action. María 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 barely fails the assessment at the end, and the ticket office asks María to return to the stadium and try some more nuggets.

María re-opens up the GLP recommendation page sees a new list of nuggets to try—the list has been updated with additional information from other learners and her own history with *Functions*. 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 María's pathway, GLP expects her to achieve at least an *"evaluating"* mastery level with it, based off of its internal model of her knowledge. The system also makes an internal note that María failed her assessment after using the three nuggets and adjusts their ratings accordingly—in the future, it will again try recommending these nuggets for other learners to see how much it helps them, and if the nuggets prove unhelpful, their ratings will decrease. Eventually they may be removed from the GLP data repository.

This time María selects a new Khan Academy video nugget from the Lower Section East – Corner that is also highly recommended, but it doesn't match her textual learning style. After watching the video, she returns to the ticket office and asks for another assessment. This time she does better and passes the assessment. Internally, GLP makes a note of this in María's learner record and also adjusts the Khan Academy nugget's rating appropriately. According to GLP's internal model of María's knowledge, it thinks she has achieved *"evaluating"* level mastery (sufficient for biologists) and marks the topic of *Functions* as "completed" on her records. She receives a ticket out of Australia.

María then returns to the GLP main page and sees the map with her pathway. Australia, and the lines connecting Australia to Cameroon and South Africa are now bright, showing her the other stadiums that she can now visit. These correspond to *Derivatives* and *Fourier Transform*, both of which have *Functions* as their pre-requisite. Furthermore, she can also still visit Ivory Coast (*Differential*), which she skipped last time—it does not have any pre-requisites.

CONCLUSION

In this paper we present Guided Learning Pathways (GLP), an asynchronous, personalized learning platform for non-traditional learners. GLP emphasizes topic-based mastery and provides learners with recommended learning materials (nuggets) that help them achieve this mastery. We describe a general framework for GLP and provide details on six potential apps: User Interface, Content Map, Content Topic Recommendation Algorithm, Learning Nuggets, and Nugget Recommendation Algorithm. In the future, other apps could be developed and integrated into the platform. Examples of each app are provided to give readers a sense of the envisioned capabilities of GLP, though one can imagine additional system functionalities. A threaded example describes how each app would interact with a single learner.

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APPENDIX – FIGURES AND TABLES

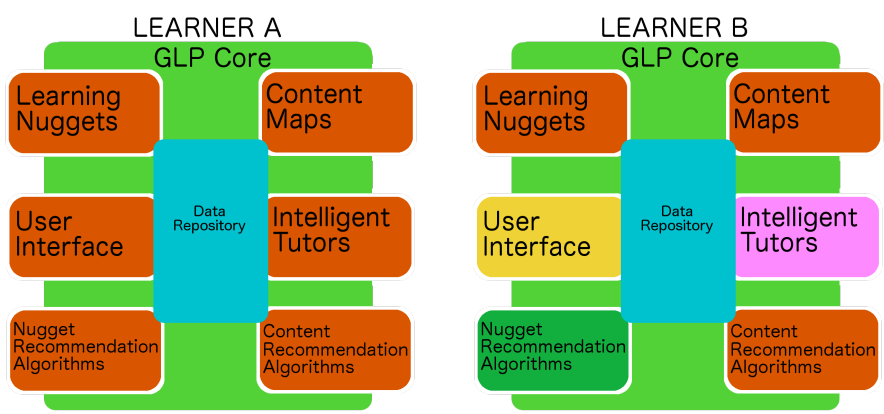


Figure 1. Different Colored Apps Come From Different Providers

Term	Definition
Content Topic	In today's terms, all subjects (such as calculus) are divided into classes that are taught over a semester. GLP eliminates the idea of a "class" and instead focuses on topics—arranged as they are conceptually related to each other instead of

	linearly, as in textbooks. These content maps look like directed, acyclic graphs, such as the Khan Academy Knowledge Map for math topics [**30**]. Content topics that are not directly related to each other can be learned in parallel. Other topics require pre-requisite knowledge that must be learned first.
Learning Nugget	Learning nuggets are the materials used to teach 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, an objective party will screen all nuggets for quality purposes. Screening of existing Open Educational Resources (OER) for quality purposes addresses some concerns that previous initiatives have found [**43**].
Pathway	Pathways are groups of content topics that move a learner towards her learning goal. They include the pre-requisite topics that need to be mastered. The learner can select to learn about topics outside of her pathway, and educators or friends can add topics. 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.

Figure 2. GLP Terms and Definitions

Learning Goal	Major Field of Study	Non-Academic Interests
Preferred Interface Style	Preferred Learning Style	Previous Knowledge

Figure 3. Learner Attributes

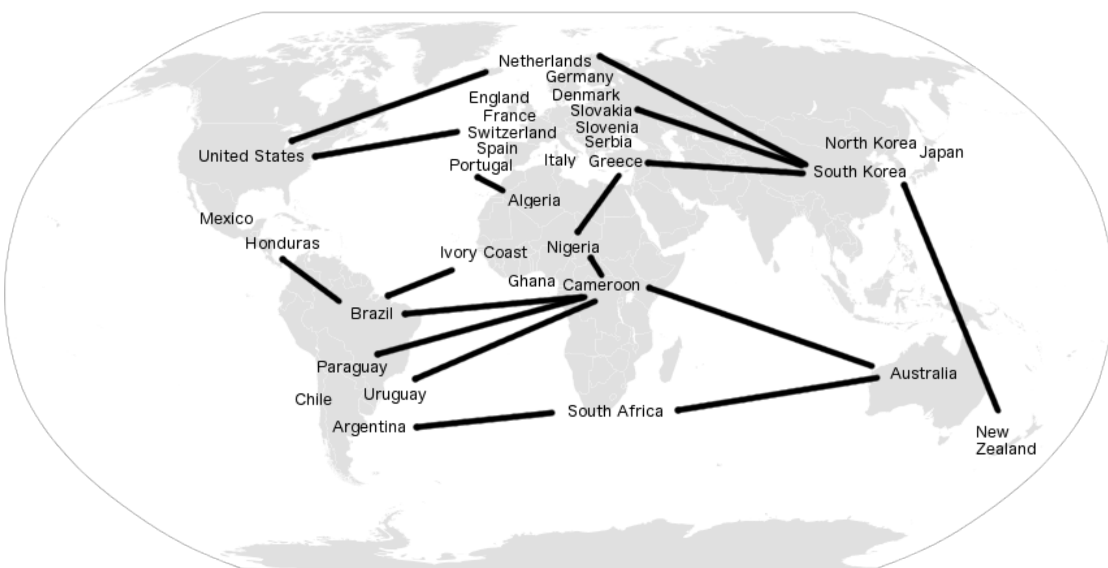


Figure 4. Example of Geographic User Interface (original image courtesy of [**44**])

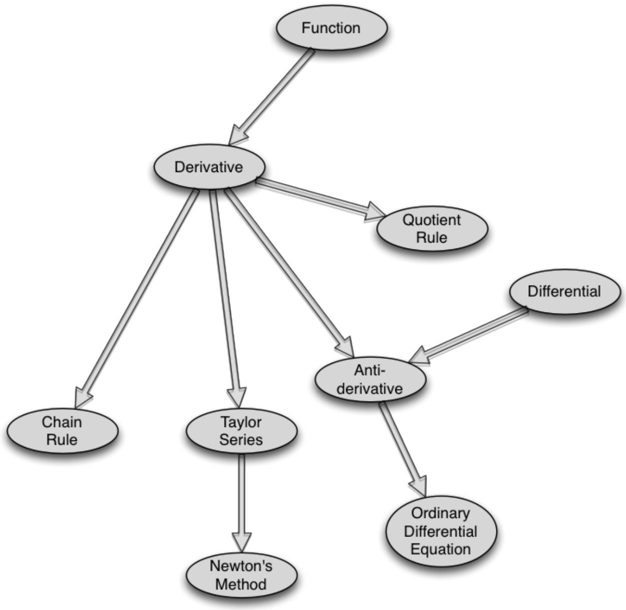


Figure 5. Subset of MIT Crosslinks Data [**35**]

Topic Name	Description	Keywords / Tags
Level of Rigor	Major(s)	Mastery Level for Pre-requisite(s)
Pre-requisite Topic(s)		

Figure 6. Content Topic Attributes

Country	Crosslinks Topic
Australia	Functions
Cameroon	Derivatives
Nigeria	Quotient Rule
Ivory Coast	Differential
Brazil	Antiderivative
Honduras	Ordinary Differential Equation
South Africa	Fourier Series

Figure 7. Blue Arrow Mapping to MIT Crosslinks

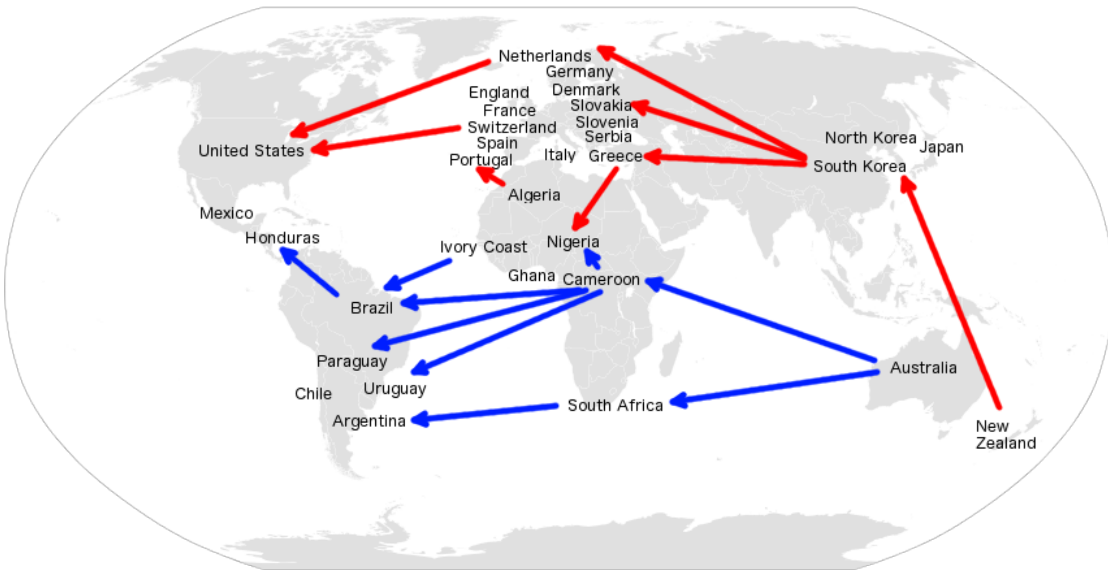


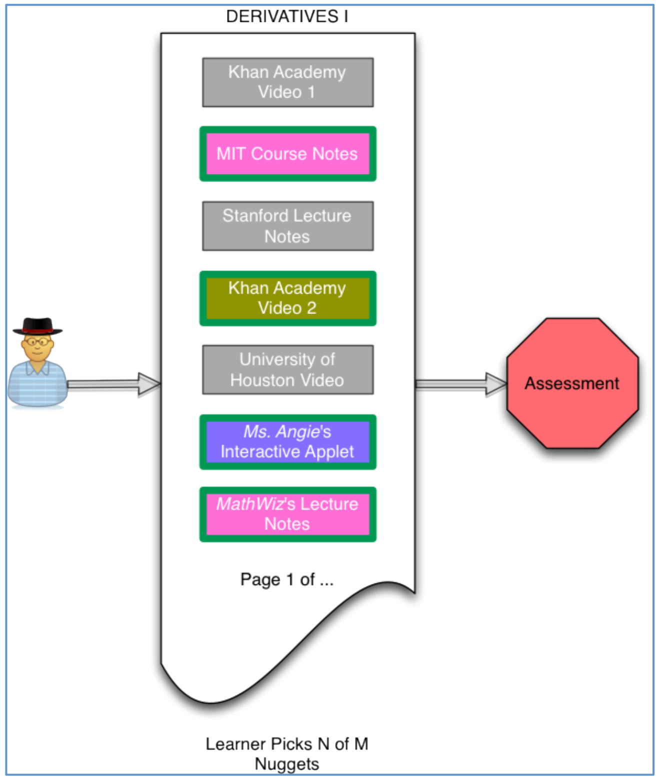
Figure 8. Example Geographic GLP Interface (original image courtesy of [**44**])

Case Studies	Example Problem	Homework
Interactive Applets	Lecture Notes	Simulations
Videos		

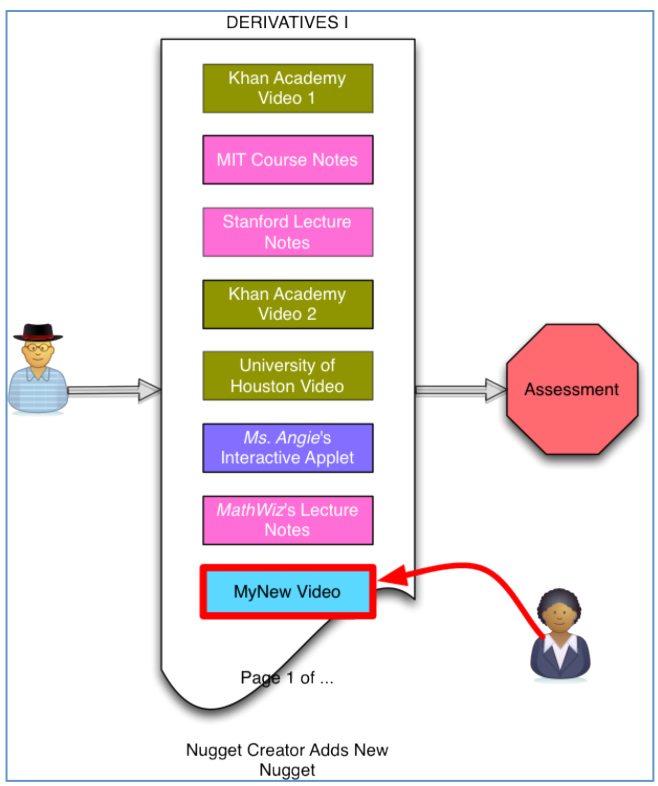
Figure 9. Example Categories of Learning Nuggets

Nugget Name	Description	Category
Content Topic	File Location	Keywords / Tags
Learning Style	Level of Rigor	Major(s)
Nugget Creator	Pre-requisite Nugget(s)	Rating

Figure 10. Learning Nugget Attributes


DERIVATIVES I
Khan Academy Video 1
MIT Course Notes
Stanford Lecture Notes
Khan Academy Video 2
University of Houston Video
Ms. Angie's Interactive Applet
MathWiz's Lecture Notes
Page 1 of ...
Assessment
Learner Picks N of M Nuggets

(a)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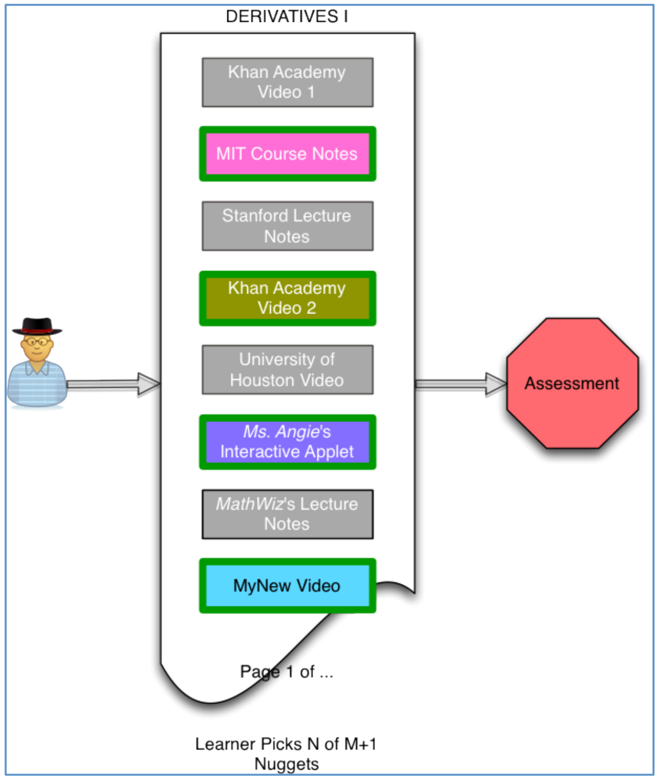
Stanford Lecture Notes
Khan Academy Video 2
University of Houston Video
Ms. Angie's Interactive Applet
MathWiz's Lecture Notes
MyNew Video
Page 1 of ...
Assessment
Nugget Creator Adds New Nugget

(b)



(c)

Figure 11. (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.