A Pedagogy/Andragogy-Neutral Learning Platform for Improving Effectiveness of Online Learning

Dr. Satish Menon,
Chief Architect/Senior Vice President,
Apollo Group, Inc.
Satish.Menon@apollogrp.edu

Introduction

Conversations about education are still dominated by discussions and discourses on what is wrong with the educational system today and how to fix it. Given the wealth of experience and research in this field, it is natural for experts to hold differing opinions on what is wrong and how to fix it. However, something the experts will agree on is the belief that individualized instruction (if it can be achieved at scale) is better than a more traditional, one-size-fits-all approach (Sprenger 2003). There is little argument that instruction or guidance, when tailored to a learner's capabilities and preferences, will be more effective (compared to the alternative) in helping a learner accomplish his/her desired goals (Sawyer 2005). In addition to helping learners reach their immediate desired goals, education should also include the development of certain core life skills, such as helping a learner developing critical thinking skills (Weimer 2002).

While significant theories and strategies exist that provide guidance on how to accomplish individualized instruction, it has been difficult to determine how to offer this instruction using technology. To date, very few systems have been able to *operationalize* the collective knowledge in this domain. Even fewer systems have provided any quantifiable *evidence* on their effectiveness, especially in a commercial setting, against a wide variety of curriculum and a large sets of learners with varied cognitive, ethnographic, and other relevant profiles. Despite much conversation about individualized instruction, a big chasm exists between research-generated insights and knowledge and the educational products offered in the market, such as learning management systems that provide learning delivery.

Our goal is the construction of a personalized, or individualized, learning platform – one that offers a great experience – an experience that is highly relevant and contextual (in relation to learners' needs and goals). We are working to create a system that provides great feedback to the learner and the teacher – a system that has the capability to support the use of the 'right' instructional strategies deemed to be optimal to accomplish the task at hand (Smith 1999). We want the system to be intelligent in turning data into actionable insights, so learners can know where they stand and what they need to do. This also enables teachers to be able to learn what works or doesn't work, and use this information as guidance.

Individualized Learning Platform

Systems in existence today can provide most of what we described above. For example, some intelligent tutors for mathematics monitor how a learner performs, and then they use that information to gauge the learner's skill level and prior knowledge (probabilistically) and adapt the instruction to help the learner achieve his/her goals. However, these techniques are very narrow in scope. Our goal is to construct an *individualized and adaptive pathway* for each learner through an entire curriculum – one that is built with the knowledge of who are the learners, what are their goals, and what are the specific skills we (the institute) want these learners to achieve, in addition to reaching specific course outcomes. Examples of these additional skills include: collaboration skills, critical thinking skills, writing skills, and more.

An individualized learning platform, by definition, is more *learner-centric.* To start with, the system models a learner – i.e. it quantifies a learner's salient characteristics that assist (or detract) him/her in their mission to learn. We call this *learner attributes.* Learner attributes are multi-dimensional – they include information about the cognitive (e.g. prior knowledge, learning styles), affective (e.g. openness, persistence), and conative (e.g. intention, resistance) (Learning Styles 2009) characteristics of the learner. Working with initial surveys, while also making implicit observations (which are easier to do in an online environment where computer interactions can be measured and analyzed), a starter set of attributes are constructed. Since cognitive attributes are dominant in the attribute set, we call this is the 'cognitive DNA' of the learner. Point to note is that, unlike biological DNA, the cognitive DNA markers easily change in values, so the system needs to measure these changes and update frequently.

Individualized serving implies that a learner has choices when working with learning instruments. Systems should provide choices for curriculum content, learning activities, and assessments. Additionally, these systems should create an online experience that is pertinent for the learner. For example, a specific topic (such as learning about calculating the net-present value of an investment in an MBA course) might have several content types available that explain the concept: PDF content from a textbook, a variety of curated online sources, a simulation, a lecture from a famous venture-capitalist explaining the concept, and more. The goal of the system is to get the learner to their 'a-ha' moment, when they understand the concept and are able to move to the next step of applying this concept. To achieve this, the system can let the learner navigate all content or the system can make a smart recommendation, based on an individual's learning style, preferences, or measured effectiveness in dealing with similar content types. This recommendation could be in the form of optional guidance - for example: '*learners like you found the following resources useful in understanding the concept', o*r, the system can provide the specific material).

Learners might require assistance over and beyond the material and instruction provided by the system and teacher. Lack of required pre-requisites, forgotten concepts, and problem-solving skills (especially in the case of adult learners who might be coming back to school after a break in education) could prevent these learners from reaching their goals. In these cases, an individualized intervention (or remediation) plan might be required. The degree of intervention could be small – can be corrected *just in time*, or it might be severe enough that a timed course (one that requires the learner to complete a course in a specific time period with a number of other learners), is required. Or, the learner might need to take a break from the class and work on updating his/her skills with a specific lesson plan, constructed by the system, while also taking required formative or summative assessments. After this work has been completed, the learner could then join another instance of this class, occurring at a later time.

An Individualized pathway is starts out as a sequence of courses and individually-constructed remediation plans that the system builds for a learner when the learner enters the program. This pathway updates as the learner progress though the curriculum. The key system capability required to build (and update) the pathway is the ability to *predict,* with a certain degree of accuracy, how the learner is likely to proceed through their educational journey. This task is not that dissimilar to how a clinical pathway is set up for a patient in the realm of personalized medicine [Alexandrou 2009] or how online advertisements work, where an online portal (such as yahoo.com) serves a banner advertisement that has a higher degree of probability of being clicked by a user. However, as one can imagine, due to the number of variables involved, an optimal pathway prediction is much more complex. To build a probabilistic prediction model, the system continually collects data (learner attributes, measured outcomes, etc.) from all interactions and tries to build a probabilistic predictive model that reveals *causal relationships* in the variables. After this model is built, the input of a set of learner attributes should yield a probabilistic set of possible outcomes – this is the information required to build an individualized pathway for the learner.

To build such a system, we needed to move the implementation of learning platforms from the realm of using only best practices to using more Evidence-Based Practice (EBP) methodologies. At every step of the way, we needed to measure and quantify the types of activities (learning activities, content, assessments, instructional strategies) proven to be effective for the different types of learners (as defined by the learner attributes).

We call such a platform '**pedagogy-neutral**', or 'andragogy-neutral' in the case of adult learners (Knowles 98), because this platform does not need to be hardwired to use any learning theory or instructional strategy – experimentation, data, and evidence will reveal the strategies appropriate for the types of learners and the topics they want to master. Needles to say, we recognized early on that this is not an easy task; if it were, someone would have already mastered it!

What makes this task difficult? Constructing a learning platform that is engaging, open, flexible, and easy to extend, while arming it with data to enable individualized serving, is a well-known art in today's systems. Large-scale social media sites, such as Facebook, have already demonstrated that it is possible to provide a great experience on top of a platform that is extensible and personal. Advertising sciences and dynamic content serving, at sites like yahoo.com, have taught us a thing or two about personalization. The complexity lies in precisely measuring and improving the effectiveness of how we serve an individual learner, enabling them to reach measurable outcomes.

Unlike similar scientific fields, such as medicine, where EBP techniques have been widely adopted, bringing EBP into the educational world has not been easy (Wikipedia 2010). One of the main difficulties lies in the impracticality of creating controlled environments to conduct research, since learning is not strictly limited to what happens in classrooms (which makes it difficult to gauge cause and effect).

Another hurdle is that unlike medical research, where subjects are observed for very long periods of time to truly determine the effects of various actions over time, most research in the educational field has been ephemeral in nature. These and other similar problems are the subject of an excellent paper by the esteemed educational psychologist, the late Dr. Ann Brown (past president of American Educational Research Association). This paper is entitled "*Design Experiments: Theoretical and Methodical Challenges in Creating Complex Interventions in Classrooms*". Dr. Brown lists a number of issues to overcome – lack of controlled environments, the need to consider complex interactions involving curriculum selection, teacher training, testing, classroom context, and the lack of using the standardization of key instruments, such as assessments.

Fortunately for us, our work is being done in an environment where some of these issues either do not exist or their effect is marginal, providing us with more of a 'clean room' than has ever existed before. Our institutions offer various degree programs for adult learners in post-secondary education (Associate, Bachelors, Doctorate, MBAs etc.) for a wide variety of disciplines. Students have a varied ethnographic mix. The student population size is large (over four hundred thousand). In some programs (which are a mix of online and campus-based), classes start every six weeks. These classes offer the opportunity to perform cross-sectional, retrospective, and longitudinal studies. This offers us the rare luxury to focus on building and deploying systems for the purpose of studying the effect of various theories and strategies.

Figure 1 below depicts a variation (with some small modifications) of Dr. Brown's suggested environment for design experiments. In the center is the Individualized Learning Platform we set out to build. Since one of our goals is to learn the effectiveness of implementing theories and strategies in an online environment, the measured "context" is a critical input into the system. Context, in this case, is defined (by Prof. Dey) as any information used to characterize the 'situation' of an entity that is relevant to the task at hand. In our case, learner context is the set of all learner-specific data, including learner attributes, goals, etc. Similarly, Teacher Context includes data about individual teachers' styles, skills, and more. Signals are data-generated as the result of interactions between the learner and all other players (peers, faculty, network. etc) and objects (curriculum, tools, etc.). Guidance can be as simple as a recommendation (e.g. 'students like you who found the current topic difficult found the following resources useful'), a just-in-time remediation plan (a sequence of topics to master before proceeding) or an individualized pathway construction or modification (e.g. learner recommendation to take a series of courses, per their goals and skills, and a remediation plan before getting to course #3).

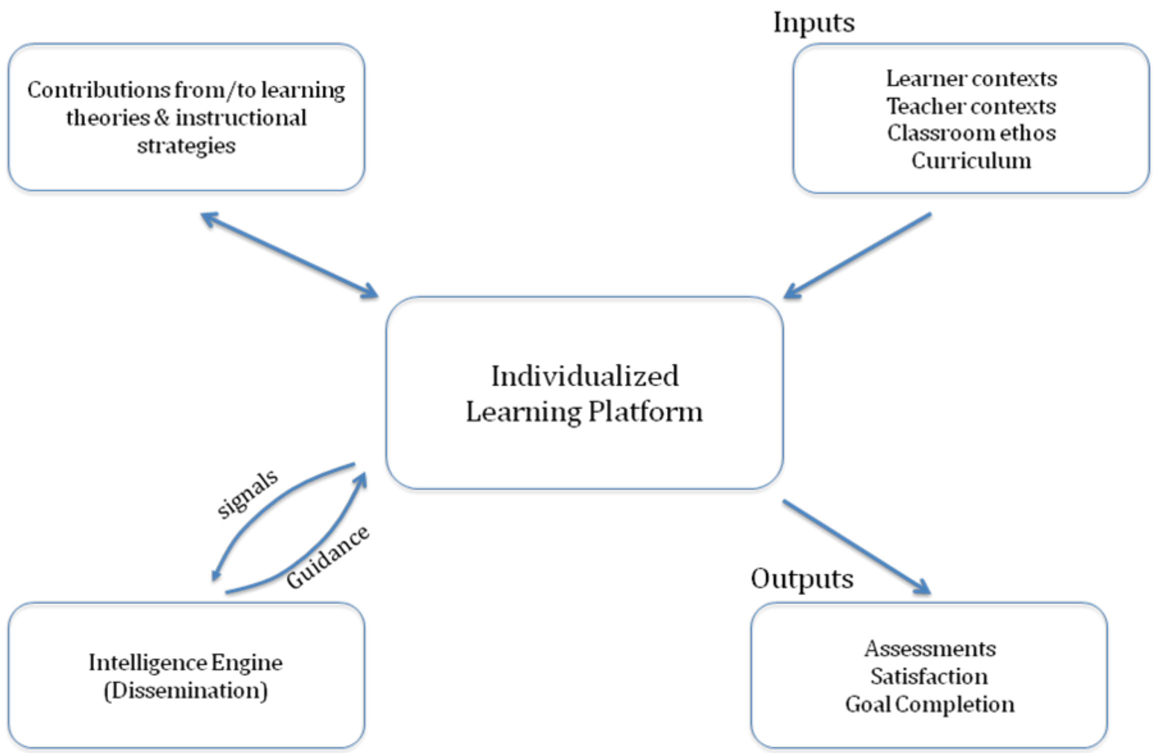

Figure 1: Overview of an Individualized Learning Platform

Core Principles Embodied in the Platform

A core set of principles, or beliefs, define the construction of any great platform. In our case, working with cognitive psychologists and educators, we distilled the research, intuitions, and our institution's experiences in serving the needs of adult learners into a small set of guiding principles. Each of the principles translates into specific platform capabilities and product features. Listed below is a partial set:

1. ***Learning is a personal journey***: This is a core tenet of ILP. As described before, this principle meant that we needed to encapsulate the essential attributes of a learner within the system, which we accomplished using the notion of the cognitive-DNA approach previously described. The information coded in cognitive-DNA enables us to guide the learner as they make their journey through their own unique experience. It did not matter to us if we got all the attributes right at first – the data and experiment-driven nature of our system eventually converge on the 'right' set of attributes (proving some attributes are more important than others). Individualized delivery also meant that we needed the platform to offers choices – instructional strategies (such as direct instruction, indirect instruction, experiential learning) and content types that suit different learning styles (such as visual, aural, verbal, logical). This requirement meant that the technology platform needed to include a variety of tools that support the implementation of these strategies (for example, synchronous and asynchronous modes of instruction, simulations, and multi-player games, text, audio, video, etc.). Finally, this principle meant that we needed to build an instrumentation system that measures and quantifies user interactions. Using machine-learning techniques that employ programs (such as categorization and classification algorithms), we obtained insight on learner types (as defined by the learner attributes mentioned above) and produced the kinds of outcomes against the experiences we serve the learners. This information is critical for us to develop and apply intervention techniques for learners.
2. ***Learning is collaborative and social***: This principle underlies learning theories, such as social constructivism, and a number of different instructional strategies, such as indirect instruction (e.g. collaborative case studies) and interactive instruction (e.g. role playing, peer-partner learning) (Gunawardena 1995). Collaborative and social aspects of learning are even more relevant now, because today's learners have become adept at interacting with their peers and friends through social networking sites. From a platform perspective, this meant we needed to construct a system that can build ad hoc networks on demand, such as a network of a learner's classmates, study groups, peers, faculty, alumni, and more, while also leveraging the network for the right pedagogical reasons.
3. ***Guidance should be evidence-based:*** This principle instructs the use of actual evidence in making a recommendation or stipulating an action. Proponents of EBP suggest that the lack of progress in the educational field is attributable to the practice of using hard scientific evidence about 'what works'. Opponents argue that hard evidence, while necessary (and possible) in fields of medicine, is not what education needs – instead, success depends on a host of factors that include the style, personality, and beliefs of the teacher and the needs of particular learners. We don't disagree with either observation, as our goal is to provide the teacher (and the system) with quantifiable insights and evidence on what works and what does not work for an individual learner. It is certainly up to the teacher to use this information or override it with personal insights – our goal as technologists is to measure, analyze, and reveal the results of any such decision that will lead to better overall decision making.

While there are a host of other principles, the above three exerted dominant influence on the construction of the platform.

Some Implementation Considerations

A core tenet of great platform construction is the belief that platforms do not dictate any specific pre-wired policies, such as, requiring all learners to take a formative assessment. Instead, a platform must provide the mechanisms (e.g. creating and delivering an assessment), but the idea of requiring a learner to take an assessment (or not) should be a policy decision, outside the purview of the platform.

The desire to be pedagogy-neutral and use data to inform 'what works' meant that we needed to be able to choose the right set of tools and techniques for the right job. This meant that our platform had to be open and extensible, allowing us to very quickly incorporate new tools or applications, as needed. However, we had to ensure that these tools and techniques interacted with the system seamlessly and provided a uniform experience to the learner. To accomplish this goal, we chose to use a standard promoted by IMS Global Learning Consortium. This standard is called Learning Tools Interoperability (LTI) and was designed to promote interoperability of learning tools. Compliance with IMS meant that we could use any educational tool provided by a third-party vendor or open source consortium, such as Sakai Project. We provided a common instrumentation and measurement framework to ensure that all the tools created a uniform set of data about user interactions.

A number of techniques used in the construction of the ILP have come from experience in other domains: construction of large-scale social platforms, cloud computing, advertising sciences, personalization, and more. Our goal was to apply these techniques in the appropriate way for this domain. We were also able to accelerate the construction of the ILP by using a wide variety of open source technologies that are widely deployed in other domains. The data gathering and processing portion of the platform were built using open source computing and a storage project called Apache Hadoop. Hadoop implements a version of the map-reduce paradigm, which is useful for processing large data sets, and was pioneered by Google. The core of the learning platform was built using open source technologies, including Apache Sling, Jack Rabbit, and more. We also made a strategic decision to maintain interoperability with the Sakai 3.0 project, which allows us to share tools and technologies with the larger community.

Conclusion

As evident from the scope, this is a complex, sizable, multi-year project that aims to provide an individualized learning experience with the goal of assisting learners to reach their desired outcome. Our expectation is that the system we have built will significantly advance the start of the art, providing a challenging, yet compelling environment, and ultimately, improving the degree completion rates for online learners. To achieve this, we took an empirical, science-driven approach to constructing an individualized learning platform. While parts of this platform have been released as features in our current online offerings, a completely new system will be launched in the fall of 2010. We will be frequently sharing our results, travails included, with the education community.

References

Alexandrou, D, Xenikoudakis, F, Mentzas, G, *SEMPATH: Semantic Adaptive and Personalized Clinical Pathways, International Conference on* eHealth, Telemedicine and Social Medicine, *Issue 1-7, Feb. 2009*

Boetcher, J 1998, *Pedagogy and Learning Strategies*, California State University at Sacramento. http://www.csus.edu/pedtech/Learning.html

Bourassa, S 1999, *Effects of child care on young children*, Proceedings of the third annual meeting of the International Society for Child Psychology, International Society for Child Psychology, Atlanta, Georgia, pp. 44-6.

Gunawardena, C.N 1995. *Social Presence Theory and Implications for Interaction and Collaborative Learning in Computer Conferences*, International Journal of Educational Telecommunications, Charlottesville, VA, pp. 147-166

Learning Styles 2009, *Overview of Learning Styles*, viewed Sep 2009, http://www.learning-styles-online.com/overview/

Sawyer, K 2005, *The New Science of Learning,* The Cambridge Handbook of Learning Sciences, Cambridge University Press, pp 1-17

Smith, M. K 1999, *the cognitive orientation to learning*, The encyclopedia of informal education, http://www.infed.org/biblio/learning-cognitive.htm

Sprenger, M 2003, *Differentiation through learning styles and memory*. Corwin Press, Thousand Oaks, CA.

Weimer M 2002, *Learner-Centered Teaching: Five Key Changes to Practice*, Jossey-Bass, A Wiley Company

Wikipedia 2010, *Evidence-based practice*, viewed July 5, 2010, http://en.wikipedia.org/wiki/Evidence-based_practice