MOOClets: A Framework for Dynamic Experimentation and Personalization

Joseph Jay Williams
Harvard University
Cambridge, MA, USA
joseph_jay_williams@harvard.edu

Anna N. Rafferty
Carleton College
Northfield, MN, USA
arafferty@carleton.edu

Samuel Maldonado
San Jose State University
San Jose, CA, USA
samuel.maldonado@sjsu.edu

Andrew Ang
Harvard University
Cambridge, MA, USA
andrew_ang@harvard.edu

Dustin Tingley
Harvard University
Cambridge, MA, USA
dtingley@gov.harvard.edu

Juho Kim
KAIST
Daejeon, South Korea
juhokim@cs.kaist.ac.kr

ABSTRACT
Randomized experiments in online educational environments are ubiquitous as a scientific method for investigating learning and motivation, but too rarely improve educational resources and produce practical benefits for learners. We suggest that software and tools for experimentally comparing resources are designed primarily through the lens of experiments as a scientific methodology, and therefore miss a tremendous opportunity for online experiments to serve as engines for dynamic improvement and personalization. We present the MOOClet requirements specification to guide the implementation of software or tools for experiments to ensure that whenever alternative versions of a resource can be experimentally compared (by randomly assigning versions), the resource can also be dynamically improved (by changing which versions are presented), and personalized (by presenting different versions to different people). The MOOClet specification was used to implement DEXPER, a proof-of-concept web service backend that enables dynamic experimentation and personalization of resources embedded in front-end educational platforms. We describe three use cases of MOOClets for dynamic experimentation and personalization of motivational emails, explanations, and problems.

ACM Classification Keywords
H.5.m. Information Interfaces and Presentation (e.g. HCI): Miscellaneous; K.3.1. Computer Uses in Education

Author Keywords
A/B experiment; dynamic experimentation; MOOClet; personalization; multi-armed bandit; reinforcement learning; statistical machine learning; adaptive learning

CHI'16, May 07–12, 2016, San Jose, CA, USA

ISBN 123-4567-24-567/08/06...$15.00
DOI: http://dx.doi.org/10.475/123_4

INTRODUCTION
One of the promises of online education is to advance research on learning, and the advantages of online educational environments for conducting randomized experiments have yielded many insights into learning and motivation.

However, it is important for academic research to yield not only generalizable principles, but result in enhancements to student learning. Unfortunately, there is a substantial delay and many obstacles between obtaining experimental results to making concrete changes to courses. Arguably, most published randomized experiments in online environments do not directly result in improvements to the context in which the study was conducted.

In contrast, when randomized experiments or "A/B tests" are used for the more practical purpose of product testing versions of websites and online advertisements, the software is designed so that the versions that maximize user engagement or purchases are provided to subsequent users [3]. Instructors and students could benefit more directly from research studies if software for educational experiments was designed to use data to dynamically transition from assigning versions of a lesson with equal probability to making it more likely that effective lessons are assigned to future students, rather than using data from an experiment in one course to impact design in a course occurring months later.

However, using data from randomized experiments to provide one version of a resource to everyone reflects a "one-size-fits-all" assumption, and could miss what are known as heterogenous effects, where one version works well for one subgroup of learners, while another version works better for a different subgroup. Experiments could therefore lead to personalization, in the sense that different conditions are presented to learners with different characteristics. This suggests one way to bridge experiments with the large body of work on adaptive learning, tailoring and personalization, although the term "personalization" can refer to many different approaches. Intelligent tutoring systems typically personalize which hints or how many activities are provided, "customization" can refer to activities like an individual entering their unique name or choosing their own learning pathways, and the recommendation of activities can be achieved by building data-intensive user models and profiles, see [2] for a review.

Despite the novel opportunities online environments provide for randomized experiments, and their widespread use, relatively little work in education has examined how to design tools for instructors and researchers to conduct experiments. The major technical work on building tools for experiments has taken place in industry settings like website testing, where companies like Facebook and Microsoft have substantial resources to hire programmers to implement experiments and code custom machine learning algorithms for product improvement, like creating programming languages for experiments [1].

UNIFYING SOFTWARE FOR EXPERIMENTATION, DYNAMIC IMPROVEMENT, AND PERSONALIZATION

Currently, largely different software and tools are used for three functions we claim can be closely related: (1) Conducting an experiment on a resource, by assigning alternative versions of the resource with equal probability. (2) Dynamically improving a resource, by adding or removing which versions are presented over time, as new ideas arise or new data is collected. (3) Personalizing a resource, by presenting different versions to learners based on characteristics like prior knowledge or motivation.

Design Goals

Software or end-user tools for conducting an online educational experiment can simultaneously enable dynamic improvement and personalization, if it is possible to:

- Add and remove versions at any point in time.
- Use multiple methods for deciding how versions are delivered to a particular learner, including but not limited to uniform randomization, weighted randomization, personalization based on a learner's characteristics.
- Change the method being used to assign versions to learners, at any point in time, such as changing the weights/probabilities or assigning a version, changing the rules for assigning based on a learner's characteristics, or both.
- Collect and access data from past learners who received alternative versions, in deciding which versions are best and dynamically improve a resource.
- Collect and use data about a specific learner, in deciding which version to assign to them, in order to personalize or tailor.

MOOClet Specification for Software for Experimentation, Dynamic Improvement and Personalization

To achieve the preceding design goals, we provide what is known as a *software requirements specification* for what components and functions should be satisfied by the software underlying an experiment on a digital educational resource. We name this the *MOOClet* requirements specification, and the

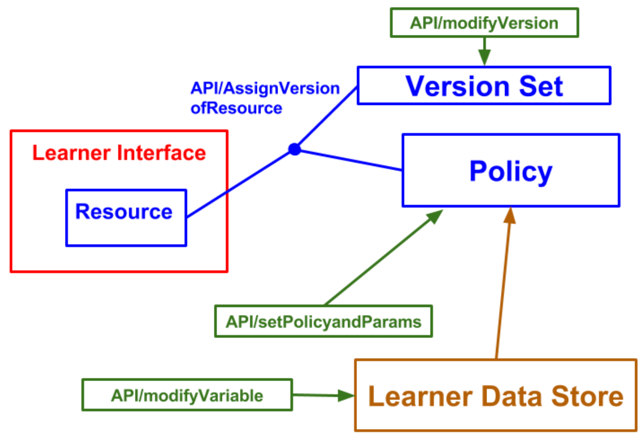

Figure 1. Components of the web service that enables an educational resource to function as a MOOClet. Before each learner interacts with the resource/MOOClet, the Learner Interface makes an API call to the web service, and the Policy associated with the MOOClet can use information from the Learner Data Store in selecting a version from the Version Set and serving it to the Learner Interface. API endpoints exist to allow addition or modification of versions and variables, and changes to the current Policy.

API (Application Programming Interface) Specification		
Endpoint	Parameters	Function
assignVersionofResource	learner_id, mooclet_id	Assign version of resource using current policy
modifyVersion	version_id, mooclet_id, version_content	Add or modify a version for a MOOClet
modifyVariable	learner_id, mooclet_id, variable, value	Add or modify variable in Learner Data Store
setPolicyandParams	mooclet_id, policy, policy_parameters	Change policy and/or policy parameters

Figure 2. The key API endpoints for the DEXPER web service. DEXPER serves as the backend pat of MOOClets by providing versions to a front-end Learner Interface, and allowing modification at any point via API of Versions, Learner Variables, and a Policy or its paramaters.

term *MOOClet*[1] is used to refer to any educational resource augmented to meet these requirements. Roughly, implementing a digital educational resource as a MOOClet associates the front-end software presenting the resource to learners with back-end software that maintains a set of versions, a store of learner data, and a suite of methods for assigning versions to learners (including weighted randomization and personalization using rules). A MOOClet must also provide functions that instructors or researchers can use at any time to modify the back-end components, such as adding new versions or learner data, and changing which method is being used to assign versions to learners.

As depicted in Figure 1, an online educational resource implemented as a MOOClet – or more formally, using the software requirements specification for a MOOClet– has the following components:

- A *Learner Interface* that displays the content a learner will interact with. The exact content the learner sees depends on which alternative condition or version of an educational

[1] We introduce the novel term *MOOClet* because it is useful to have a label for educational resources that match this precise specification, versus educational resources that only enable randomized experimentation, or only enable personalization. The approach applies to any digital educational resource, and to digital resources beyond education. from websites to emails to mobile apps. Another term we have used is *AdapComp*, short for Adaptive Component.

resource they are assigned to. For example, one of two explanations for why the answer to a problem is correct. This is what would typically be called an educational resource, since there is usually just one version when no experiment is being conducted.

- A *Version Set* data structure that contains the alternative versions of content that will be provided in the Learner Interface. For example, this structure could contain multiple different explanations a learner could be shown. Elements of the Version Set can be accessed, modified, and added at any point.
- A *Learner Data Store*, which contains a set of variables linked to each learner by their anonymous learner ID. This might include whether a learner had gotten a previous problem right, or their rating of an explanation. Variables can be added and modified at any point. All variables can be accessed and used by the *Policy* that determines which version is assigned to a particular learner.
- A *Policy*, which is a function for determining which version of a resource is presented to a particular learner, and can use any data in the *Learner Data Store*, about the current learner or the effects of versions on past learners. A MOOClet must always have access to the *Randomized Personalization* Policy Class, which enables uniform randomization, weighted randomization, personalization using IF-THEN rules. Particular instantiations of software for MOOClets can optionally provide a range of other Policy Classes.

DEXPER Web Service for enabling resources to function as MOOClets

We used the MOOClet specification to implement a proof-of-concept web service that enables cross-platform dynamic experimentation and personalization, which we call DEXPER. DEXPER can be used with text and HTML components of educational resources, which are ubiquitous across platforms and play an important role in learning, such as motivational messages, explanations, and problems or quizzes.

DEXPER is implemented using Django (a python-based framework for web applications), with classes that allow the creation and modification of SQL database objects for text and HTML versions that are needed for a MOOClet's *Version Set*, variables and values that make up the *Learner Data Store*, and a range of Policy Classes. These components of the MOOClet can all be added or modified using a set of RESTful API calls, a specification of which are shown in Figure 2. We also use built-in Django capacity to provide a graphical user interface that allows manual editing of these database objects.

The DEXPER Policy Classes allow weighted random assignments (e.g., from [0.50, 0.50] to [0.20, 0.80] to [0.0, 1.0]). The weightings can be dependent on characteristics of the learner to combine experimentation and personalization (as shown in Figure 3). It also includes a policy for dynamic improvement using Thompson sampling, a multi-armed bandit algorithm from reinforcement learning [4]. In this policy, a target outcome variable from the Learner Data Store is identified, and the algorithm chooses condition assignments to maximize this value of this variable across learners. At any point an API call can be used to change the Policy being used for a specific MOOClet (or equivalently, to change the Policy's parameters). Figure 3 shows the use of specific Policies in the use cases discussed in the next section.

MOOClets provide an abstraction for reinforcement learning

More generally, the MOOClet specification serves as an abstraction for any reinforcement learning algorithm to provide the Policy for a MOOClet. To use the terminology of RL, Actions correspond to Versions, a State Space to learner characteristics in the Learner Data Store, and Reward functions to data in the Learner Data Store about past learners' responses to versions. To provide extensibility so that any machine learning researcher or service can provide policies for a MOOClet/experiment, DEXPER provides a Policy that functions as a pass-through. This Policy sends data from the Learner Data Store to another API or code base to obtain a recommendation, and then allows the external method to specify which version DEXPER selects and sends to the Learner Interface. For example, future work can use algorithms for *contextual* bandits to take characteristics of learners into account.

APPLICATIONS OF MOOCLETS

This section describes three educational resources that were implemented as MOOClets, which illustrate the use of the requirements specification and DEXPER.

Use Case 1: Personalizing Emails. Learners in a MOOC were sent emails that elicited feedback about why they were not continuing with a course [4]. Different introductory messages to the emails were written, with the goal of maximizing the number of people providing feedback. The *Version Set* consisted of three different versions of email content (conditions in experiment) differed in the introductory line, labeled Survey, Acknowledgement, Brief. The survey/emailer software Qualtrics functioned as the Learner Interface, and was used to send emails and provide the survey to collect learners' feedback. The Number of Days Active for each learner was obtained from the MOOC provider and sent via API to the Learner Data Store, in which all learners were identified by an anonymous ID (that could be connected by us to their email address). The outcome variable, Provided Feedback, was whether or not a learner responded to an email within one week. The value of this variable was added to the Learner Data Store every time a participant finished a survey, via an API call from the survey software Qualtrics.

The first batch of 1883 learners were assigned to emails with equal probability, using the Policy Weighted Randomization with parameters [0.33, 0.33, 0.33*]. The second batch of 1882 learners were assigned to emails using two policies. The first policy was to "roll out the best version" by using WeightedRandomization[0, 0, 1] to assign only the version with the highest response rate from the first batch of learners, the Survey message. This produced a response rate of 10.4%. The second policy was to personalize to subgroups of learners, since analyzing data from the first batch reveleaed a "crossover" effect. Learners with high course activity were most likely to respond

	Use Case 1	Use Case 2	Use Case 3
Learner Interface	Emailer Software (Qualtrics)	LTI Tool for quizzes, embedded in Canvas LMS	iframe in MOOC platform (edX)
MOOClet	Introductory Message to Email	Explanation	Problem
Version Set	HTML	Plain Text	URL
Policy	1. Weighted Randomization with different parameters [p1, p2, p3] resulted in: (a) Uniform choice of Versions 1, 2 or 3, [0.33*, 0.33*, 0.33*], (b) Drop V1, favor V3 over V2, [0, 0.49, 0.51] (c) Only V3, [0, 0, 1] 2. Personalization [Weighted]: IF Number of Days Active = 0 THEN Version 3 [0, 0, 1]; IF Number of Days Active = 1 THEN Version 3 [0, 0, 1]; IF Number of Days Active >= 2 THEN Version 2 [0, 1, 0].	Dynamic Randomization with target variable [Rating of Explanation Helpfulness]	External Policy: BKT - Bayesian Knowledge Tracing
Learner Data Store	Number of Days Active, Provided Feedback	Rating of Explanation Helpfulness	Accuracy on Previous Problems

Figure 3. Overview of three uses cases for a MOOClet, showing what played the role of Learner Interface, Version Set, Policy, and Learner Data Store.

to the highest rate to the Acknowledgement message, but learners with lower course activity were most likely to respond to the Survey message. Using this *Personalization* Policy resulted in 11.2% of learners providing feedback. This increase of 0.8 in response rate corresponded to a 7.6% advantage of Personalization over choosing the apparently "best" condition.

Use Case 2: Dynamic Explanations. To provide learners with explanations of why the answer to a math problem is correct, [5] report the design and evaluation of a system that automatically enhanced the explanations learners received in math problems by crowdsourcing written explanations from learners, presenting them to future learners, and dynamically choosing the most highly rated. Anyone can create systems like this using DEXPER and MOOClets. We reimplemented the displayed explanation as the Learner Interface to a MOOClet. The *Version Set* contained different versions of explanations. The variables added to the *Learner Data Store* included: the version/explanation assigned to each learner, and each learner's rating of the explanation they received. The *Policy* was DEXPER's DynamicRandomization, with the variable to optimize being learners' rating of a Version of an explanation.

Use Case 3: Problem Recommendation. We used DEXPER and MOOClets to provide individualized recommendation of problems for students in a MOOC, based on a student's performance on prior problems. The Learner Interface is provided by an LTI tool that allows the embedding of various problem "windows" inside an edX MOOC. The problems displayed in a window were native edX content, but the MOOClet allowed an external web service to decide *which* problem was displayed. This was enabled by the Version Set of a MOOClet containing *links* to individual problems rather than the content (edx problem/xblocks URLs). Then, DEXPER allowed problem recommendation to be outsourced to an external web service. An organization provided an API to receive problem recommendations based on their implementation of Bayesian Knowledge Tracing, which obtained a user's variables from the Learner Data Store, such as performance on past problems and other course activity like video watching.

Conclusion. This paper presents the *MOOClet* requirements specification for designing software for experimentation, so that every randomized comparison of versions of a resource enable dynamic improvement and personalization of that resource. We created an API accessible proof-of-concept web service, DEXPER, that provided the back-end components of a MOOClet: Version Set, Learner Data Store, and a suite of Policies. We described three applications of MOOClets and DEXPER: to experiment on and personalize emails to MOOC learners, automatically improve learners satisfaction with explanations in math problems, and adaptively tailor problems in a MOOC based on a learner's past performance on problems.

REFERENCES

1. Eytan Bakshy, Dean Eckles, and Michael S Bernstein. 2014. Designing and deploying online field experiments. In *Proceedings of the 23rd international conference on World wide web*. ACM, 283–292.
2. Peter Brusilovsky and Christoph Peylo. 2003. Adaptive and intelligent web-based educational systems. *International Journal of Artificial Intelligence in Education (IJAIED)* 13 (2003), 159–172.
3. Ron Kohavi, Roger Longbotham, Dan Sommerfield, and Randal M. Henne. 2009. Controlled experiments on the web: survey and practical guide. *Data Mining and Knowledge Discovery* 18, 1 (2009), 140–181. DOI: http://dx.doi.org/10.1007/s10618-008-0114-1
4. Jacob Whitehill, Joseph Jay Williams, Glenn Lopez, Cody Austun Coleman, and Justin Reich. 2015. Beyond prediction: First steps toward automatic intervention in MOOC student stopout. *Available at SSRN 2611750* (2015).
5. Joseph Jay Williams, Juho Kim, Anna Rafferty, Samuel Maldonado, Krzysztof Z Gajos, Walter S Lasecki, and Neil Heffernan. 2016. AXIS: Generating Explanations at Scale with Learnersourcing and Machine Learning. In *Proceedings of the Third (2016) ACM Conference on Learning at Scale*. ACM, 379–388.