Probabilistic Use Cases: Discovering Behavioral Patterns for Predicting Certification

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ABSTRACT

Advances in open-online education have led to a dramatic increase in the size, diversity, and traceability of learner populations, offering tremendous opportunities to study detailed learning behavior of users around the world. This paper adapts the topic modeling approach of Latent Dirichlet Allocation (LDA) to uncover behavioral structure from student logs in an MITx Massive Open Online Course, namely, 8.02x: Electricity and Magnetism. LDA is typically found in the field of natural language processing, where it identifies the latent topic structure within a collection of documents. However, this framework can be adapted for analysis of user-behavioral patterns by considering user interactions with courseware as a "bag of interactions" equivalent to the "bag of words" model found in topic modeling. By employing this representation, LDA forms probabilistic use cases that clusters students based on their behavior. Through the probability distributions associated with each use case, this approach provides a interpretable representation of user access patterns, while reducing the dimensionality of the data and improving accuracy. Using only the first week of logs, we can predict whether or not a student will earn a certificate with 0.81±0.01 cross-validation accuracy. Thus, the method presented in this paper is a powerful tool in understanding user behavior and predicting outcomes.

Author Keywords

Latent Dirichlet Allocation; Student Behavior; Use Case Modeling; Massive Open Online Courses

ACM Classification Keywords

I.5.2 Design Methodology: Feature evaluation and selection

INTRODUCTION

Massive Open Online Courses (MOOCs) create a tremendous opportunity to study learning from the perspective of large and diverse populations of students. In the first year alone, HarvardX[1] and MITx[2] courses, enrolled roughly 600,000 unique users from around the world [11]. Such large numbers, combined with diverse backgrounds and enrollment motivations, implies variation in how users choose to interact with material. Clickstream data – stored records of user interactions with course content – provide the opportunity to understand such variation. Previous studies have aggregated clickstream data to inform broad metrics such as the unique number of resources accessed within a course [5], while others offered more detailed activity such as pause and play clicks within a single lecture video [14]. There is no doubt these data contain a great deal of insight into student behavior, but enumerating all possible student-interaction patterns is nearly impossible. Furthermore, interpreting such patterns remains a daunting task for researchers and course teams alike.

In this paper, we make the problem of modeling student behavior more tractable by adapting the approach of Latent Dirichlet Allocation (LDA) [4]. LDA is a unsupervised probabilistic model, which has had great success illuminating shared topics in large collections of texts [2, 3, 4]. Along with natural language processing, LDA has been successfully adapted in areas such as genetics [19] and web page recommendation [26]. In the case of web page recommendation, LDA discovered latent topics associated with the semantics of user URL access patterns, all while delivering better performance compared to conventional clustering techniques [26]. Inspired by these adaptations, we use LDA to distill user interactions in an educational context by considering user interactions with resources making up a course.

Our adaptation of LDA results in a finite set of use cases representing the probability distributions of a participant interacting with each resource in the courseware. Unlike other approaches, behavioral patterns can be deduced directly from the most probable resources within a use case. Within any digital course containing unique resource identifiers, these probabilities offer a natural interpretation of behavioral patterns in a course for content curators and researchers. An additional feature of LDA is the mixed-membership model, where student behavior is represented as different proportions of a shared set of use cases, rather than hard cluster assignments. This enabled us to compare students by their relative proportions, define behavioral patterns, and effectively reduce the dimensionality of the data for further analysis and

[1] Harvard University's institution for creating MOOCs
[2] MIT's institution for creating MOOCs

prediction. Detecting such patterns is important to handle the openness of MOOCs, which has been tied to a variety of behavioral patterns, as evidenced by large initial enrollments, low percentages of completions, and widely varying resource use [17, 11, 22].

In this paper, we adapt LDA to edX clickstream data in order to address the following two questions:

- Can LDA serve as an unsupervised approach for discovering the behavioral trends of MOOC participants?
- Can the mixed-membership model from LDA predict certification?

Our application involves one MITx MOOC, an introductory physics course called 8.02x: Electricity and Magnetism.

The remainder of the paper continues as follows. The Related Work section offers a summary of work related to modeling learner behavior as context for our work. The Course Studied and Dataset section overviews the data examined in this paper. The Methods sections describes the theory behind LDA and how it is adapted to and evaluated in an educational context. The Results section provides the outcome from applying LDA to 8.02x from the spring of 2013. The Conclusion section summarizes the key contributions of this paper.

RELATED WORK

Understanding student behavior has been a consistent theme in MOOC research. Most studies aim to group students by their behavior, and then better understand how discovered behavior leads to educational advancement. A central challenge to any study includes significant aggregation of raw data sets, often requiring advanced methods that scale to large data sets.

Many researchers have employed machine learning and pattern recognition techniques to distill raw clickstream data into more interpretable models of student behavior. Kizilcec et al. [16] applied clustering techniques to gain insight into student disengagement or course completion. They represented students by their weekly activity, capturing whether or not students were “on track”, “behind”, “auditing”, or “out” each week. Using this feature representation, they performed k-means clustering and constructed four learner subpopulations: “completing”, “auditing”, “disengaging”, and “sampling”. These student subpopulations were then compared in terms of their demographics, surveyed experience, forum activity, and video streaming index to analysis retention. Rameh et al. [20] used the graphical model of Probabilistic Soft Logic (PSL) for distinguishing between forms of engagement in MOOCs. In contrast to Kizilcec et al., Rameh et al. viewed engagement/disengagement as latent variables and focused on social behaviors such as posting and subscribing in addition to more traditional behaviors such as following course material and completing assessments. Their study illustrated the informative role peer-to-peer interactions can play in user modeling. With a similar methodology Yang et al. [27] used social behavior for use in a survival analysis of students in MOOCs, finding that social engagement within the course was correlated with retention.

Preceding MOOC research, the educational data mining community has pursued a broad range of techniques in modeling student behavior and outcomes. Kardan and Conati [13] used the k-means algorithm to group students via their logs in an interactive visualization program for learning Artificial Intelligence. From the resulting groups, association rule mining was used to derive the learning behavior of these clusters and train a classifier to distinguish between high and low learners. In a learning-by-teaching environment with 40 eighth grade students, Kinnebrew and Biswas [15] combined sequence and episode mining techniques to categorize students as high or low performance as well as identify periods of productivity and counter-productivity for each student. McCuaig and Baldwin [18] also focused on performance and employed decision trees to divide up the space of learners and predict final grades. They used a mix of digital logs, formal observations, and self-assessment to create a holistic understanding of their 122 participants in a C programming class. Finally, building on the initial work of Kardan and Conati [13], Davoodi et al. [7] used the combination of k-means clustering and association rule mining to evaluate user behavior in an educational game, finding that students with more prior knowledge were more engaged in the game.

In this paper, we provide another perspective. Rather than rigidly defined feature sets, we use LDA to uncover behavioral patterns directly from the data in a unsupervised manner. This preserve much of the statistical information from the original dataset, while still forming an interpretable representation. Unlike many of the studies above, we don’t sacrifice much granularity for interpretability.

COURSE STUDIED AND DATASET

8.02x: Electricity and Magnetism is an MITx MOOC offered by edX in the spring of 2013, based on the second semester of an introductory physics course at MIT. The resources in 8.02x included a variety of videos, problems, textual content, and simulation activities. To promote engagement and self-assessment, weekly lectures were typically broken into roughly 5-10 video segments, each interspersed with graded multiple choice questions. A course structure guide indicating resource density and weight toward final grade is provided in Figure 1. Major assessment included weekly homework (18%), interactive simulations with concept questions (2%), and examinations - three midterms (15% each) and a final (30%). Other supplemental components included problem-solving videos, an eTextbook, and a threaded discussion forum. Certification was granted to for students scoring greater than 60% on graded course components. The course ran for 16 weeks, equivalent to the length of the semester long course at MIT.

Between January, 17th and September 8th, enrollment reached 43,758 people (note, registration remains open to date), with participants coming from around the world and representing a wide range of educational backgrounds [21]. Courseware interactions from these enrollees led to 37,394,406 events being recorded in the edX tracking logs [23]. Courseware in this context refers to the individual learning components and software features available to 8.02x

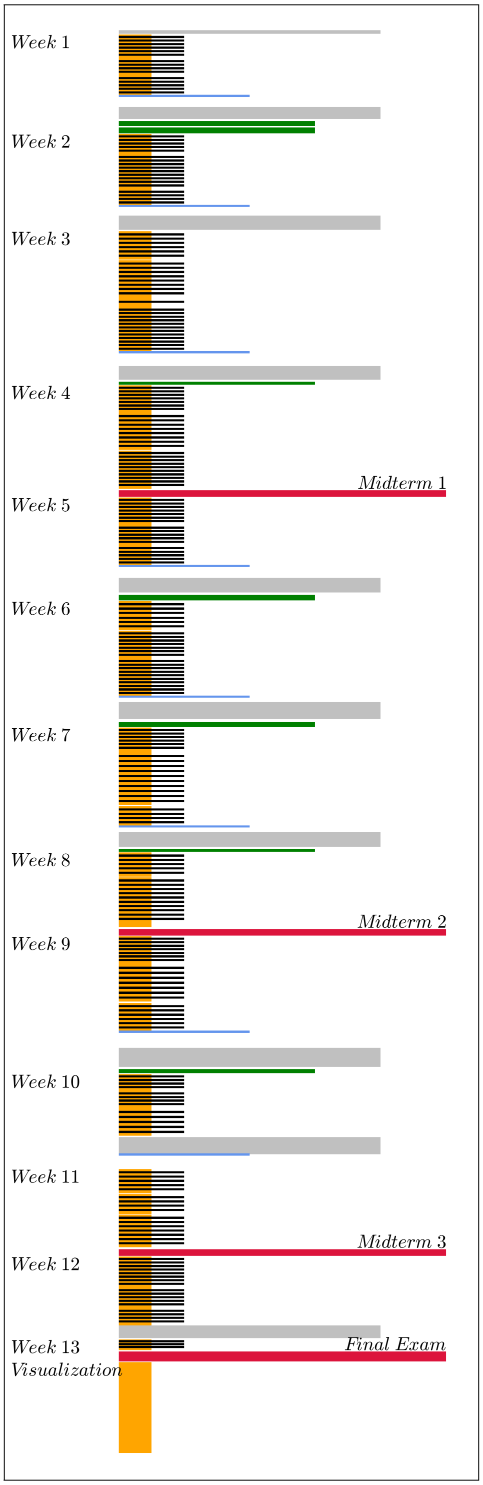
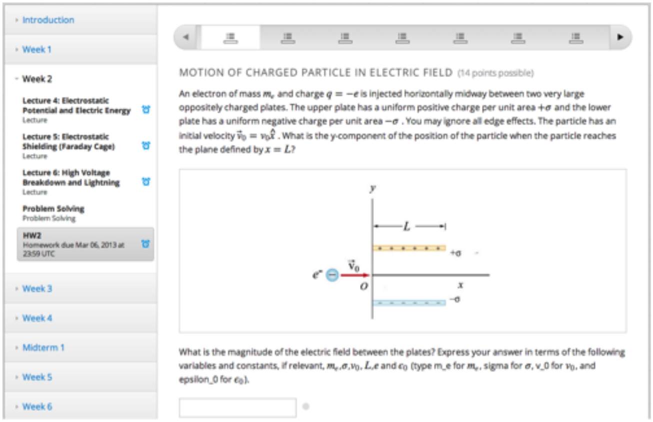


Figure 1: Course structure visualization. Each bar is a set of resources, where color and length represents the type of resource and its weight toward final grade, respectively. Orange - lecture videos, black - lecture questions, gray - homework, green - TEAL simulations, red - exams, and blue - problem solving videos.

participants. In this study, only components making up the backbone of 8.02x were analyzed. This included chapters, sequences, verticals, problems, videos, and html pages. Courses on the edX platform are organized hierarchically, so components are nested inside one another. Chapters, sequences, and verticals are container objects that form organizational units in the course. Generally, chapters contain sequences, which in turn contain verticals. Within these containers are the course resources [8].

In order to better understand the course structure of 8.02x, a screenshot is provided in Figure 2. Unique resources are navigated in two ways: the left navigation bar provides a link to sequences of content that are organized into chapters (represented by weeks of material), while the top navigation provides access to individual resources and verticals. More information about 8.02x can be found at www.edx.org.


Introduction
Week 1
Week 2
Lecture 4: Electrostatic Potential and Electric Energy
Lecture
Lecture 5: Electrostatic Shielding (Faraday Cage)
Lecture
Lecture 6: High Voltage Breakdown and Lightning
Lecture
Problem Solving
Problem Solving
HW2
Homework due Mar 06, 2013 at 23:59 UTC
Week 3
Week 4
Midterm 1
Week 5
Week 6
y
L
+σ
e^-
$\vec{v}_0$
O
x
−σ

MOTION OF CHARGED PARTICLE IN ELECTRIC FIELD (14 points possible)

An electron of mass m_e and charge $q = -e$ is injected horizontally midway between two very large oppositely charged plates. The upper plate has a uniform positive charge per unit area $+\sigma$ and the lower plate has a uniform negative charge per unit area $-\sigma$. You may ignore all edge effects. The particle has an initial velocity $\vec{v}_0 = v_0\hat{x}$. What is the y-component of the position of the particle when the particle reaches the plane defined by $x = L$?

What is the magnitude of the electric field between the plates? Express your answer in terms of the following variables and constants, if relevant, m_e,σ,v_0, L,e and ϵ_0 (type m_e for m_e, sigma for σ, v_0 for v_0, and epsilon_0 for ϵ_0).

Figure 2: Screenshot of student display for 8.02x courseware. The left navigation bar provides access to weekly chapters, while the main display, to its right, offers videos, problems, and html pages packaged in lecture, problem, and tutorial sequences.

METHODS

This section explains how LDA is adapted to model user behavior in MOOCs as well as the processes used to predict certification. Beginning with an overview of the theoretical background of LDA, we cover its original use for topic modeling in natural language processing [4] and draw a parallel between topic modeling and user modeling, which forms the basis for probabilistic use cases. Following this introduction, alternative definitions for quantifying interactions with course modules are explained. These alternatives are evaluated according to their ability to predict certification, which is explained subsequently along side the evaluation process for LDA.

LDA for Traditional Topic Modeling

Traditionally, LDA has been used to understand the latent topic structure of textual documents. Topics are thought of as probability distributions over a fixed and shared vocabulary. LDA is an unsupervised technique, meaning initially there are no keywords or tags that could be used for categorization by topic. Hence, the topics, their distributions, and the topic assignments of each word are hidden variables that need to be estimated. These hidden variables are combined with the observable variables – document word counts for each word of the fixed vocabulary – to form a generative process that defines a joint distribution over the hidden and observable variables. This distribution is used to form a posterior distribution for the hidden variables that is optimized through an approximation to the Expectation-Maximization (EM) Algorithm [3, 4].

More formally, LDA assumes there are K topics in the collection of T documents that have a fixed vocabulary (V). These topics are indexed by $\hat{z} = 1, ..., K$ and represent a probability distribution over V called $\beta_{\hat{z}}$, where each word ($\hat{w}$) has a probability $\beta_{(\hat{w}|\hat{z})}$. Each document ($d^t$) in the collection can be represented as a bag of n_t words, i.e. $d^t = ({w_1}^t, ..., {w_{n_t}}^t)$. Although all of the documents share the same set of topics, each document has its own topic proportions (θ^t). θ^t is a categorical distribution sampled from a Dirichlet distribution with parameters α, where $\theta^t_{\hat{z}}$ is the probability of topic $\hat{z}$ in document d^t. This categorical distribution in turn is the basis for a multinomial distribution used to assign each word in d^t to a topic, i.e. $z^t_1, ..., z^t_{n_t}$. Using this formulation gives rise to the graphical model shown in Figure 3.

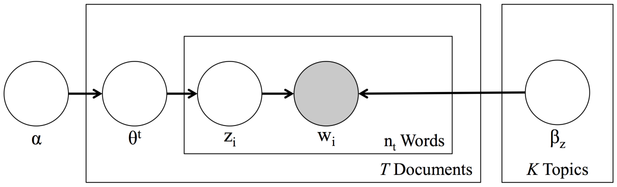


Figure 3: The graphical model for Latent Dirichlet Allocation [4] when applied to topic modeling. Each node represents a random variable. The hidden variables for the topic distributions (θ^t), topic assignments (z_i), and topics (β_z) comprise the unshaded nodes, while the observed words (w_i) are shaded. The plates represent replicates for the n_t words, T documents, and K topics.

Unfortunately, the posterior distribution for hidden variables defined by LDA is normally intractable because of the marginal distribution for the documents [4]. To approximate a solution, we use the python package gensim [9], which implements an online variational Bayes algorithm as proposed by Hoffman et al. [12].

LDA for Probabilistic Use Cases

In order to model behavior, we represent students as a bag of interactions with the courseware. Each of the static resources in the backbone of a course, as defined in the course studied and dataset section, has a unique module identifier. These module identifiers ($\hat{m}$) form a fixed course vocabulary or structure ($\hat{m} \in C$) for LDA. In 8.02x, there were 1,725 unique module identifiers. With this information, a student in a course with T registrants can be modeled as $s^t = (m^t_1, ..., m^t_{n_t})$, where m^t_i represents an interaction with a course module. By substituting the collection of documents with students in a course, topics described behavioral patterns rather than words. For clarity, we chose to refer to these interaction-based topics as *probabilistic use cases*. As such, use cases are similarly indexed by $\hat{u} = 1, ..., K$ and define a probability distribution over C called $\beta_{\hat{u}}$, where each module has an interaction probability of $\beta_{\hat{m}|\hat{u}}$. Students, like documents, share the same set of use cases, but in different proportions defined by ϕ^t. With this construction, Figure 4 describes a graphical model that is parallel to the topic modeling application. This model builds on the existing infrastructure in place for topic modeling and allows us to investigate the hidden behavioral structure within a course.

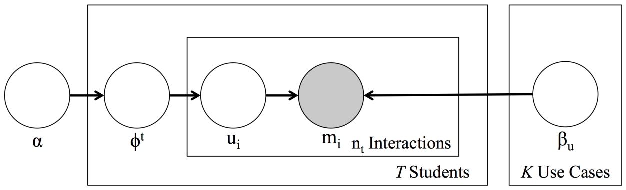


Figure 4: The graphical model for Latent Dirichlet Allocation when applied to use case modeling. Every node represents a random variable. The hidden variables for the use case distributions (ϕ^t), use case assignments (u_i), and use cases (β_u) are represented by the unshaded nodes, while observed course interactions (m_i) are shaded. The plates represent replicates for the n_t interactions, T students, and K use cases.

Interaction Representations

In applying LDA to model the behavior of MOOC participants, each student is represented as a bag of interactions with the courseware, where we only consider browser issued events. In order to quantify these interactions, we considered the three following representations:

- **Binary indicators** that are 1 if the student ever visited the module and zero otherwise.
- **Counts** of the browser events logged by a student for a specific module.
- **Time spent** in seconds on each course module, where time is calculated by taking the difference between browser event timestamps. Breaks over 30 minutes long were discarded.

Binary indicators and word counts are common in the traditional topic modeling applications, while time spent is unique to the context of modeling user behavior.

Evaluating Interaction Representations

Each representation was tested based on its ability to accurately predict whether or not a student would earn a certificate. For each week in 8.02x's 18 week runtime, we separately generated each of the interaction representations using the logs from the beginning of the course to the end of the given week. The performance of each representation was quantified by 5-fold cross validation of a Support Vector Machine (SVM) classifier for certification, where Different Error

Costs (DEC) compensated for the class imbalance [24]. The representation that performed the best across these weekly prediction tasks served as the bag of interactions for fitting LDA, saving us from having to consider each interaction representation for a varying number of use cases. This also provided a baseline to compare the predictive performance of a student's use case proportions (ϕ^t).

Evaluating Probabilistic Use Cases

Using the best interaction representation from the above process, LDA was evaluated on how well it modeled the data in addition to it's predictive performance. Traditionally, model selection, i.e. selecting the optimal number of use cases, is based upon log perplexity [4] per interaction. This method is equivalent to the negative log likelihood of a corpus (approximated by the Evidence Lower Bound) divided by the number of interactions within that corpus, as in equation 1.

$$log\{perplexity(corupus)\} = \frac{-log\{P(corpus|\alpha, \beta)\}}{\sum_{corpus} n_t}. \tag{1}$$

This is commonly used in natural language processing to evaluate language models. We use log perplexity per interaction here to reduce perplexity to a reasonable numerical scale.

Using the models that fit well without an excessive number of use cases, we evaluated how well LDA predicted outcomes like certification. LDA was trained on a weekly basis, where only the logs from the beginning of the course to the end of the given week were used. Students were then represented by their use case proportions (ϕ^t) in the 5-fold cross validation of a Support Vector Machine (SVM) classifier for certification, where Different Error Costs (DEC) compensated for the class imbalance [24]. This approach demonstrated the predictive power of a student's use case proportions (ϕ^t) and quantified the effect that varying the number of use cases has on performance.

RESULTS

The results from applying LDA to 8.02x are broken into 4 section. Selecting an Interaction Representation compares the various interaction representations. Employing the optimal representation, the Identifying the Number of Use Cases Through Log Perplexity section explores how well LDA fits the data for a varying number of use cases. The Probabilistic Use Cases section visualizes and explains the resulting use cases through their probability distribution over the course structure. In the final section, Predicting Certification, students' use case proportions are used in order to predict certification.

Selecting an Interaction Representation

A student's activity within the edX platform can be quantified in a number of ways. In this section, we compare the the ability of our activity representations – binary indicators, interaction counts, and time spent on each module – to predict certification of students. In this section, binary indicators, interaction counts, and time spent on each modules are compared based on their ability to predict certification of students.

	Indicators		Counts		Time Spent	
Week	TNR	TPR	TNR	TPR	TNR	TPR
1	0.99	0.00	0.92	0.33	0.92	0.38
2	1.00	0.00	0.96	0.36	0.95	0.39
3	1.00	0.00	0.98	0.40	0.97	0.39
4	1.00	0.00	0.98	0.44	0.98	0.45
5	1.00	0.00	0.98	0.52	0.98	0.48
6	1.00	0.00	0.98	0.57	0.98	0.54
7	1.00	0.00	0.98	0.65	0.97	0.76
8	1.00	0.00	0.97	0.79	0.97	0.81
9	1.00	0.00	0.98	0.82	0.97	0.91
10	1.00	0.00	0.98	0.83	0.97	0.91
11	1.00	0.00	0.97	0.93	0.97	0.93
12	1.00	0.00	0.97	0.94	0.97	0.94
13	1.00	0.00	0.97	0.94	0.97	0.95
14	1.00	0.00	0.97	0.95	0.97	0.95
15	1.00	0.00	0.97	0.96	0.98	0.96
16	1.00	0.00	0.97	0.96	0.98	0.96
17	1.00	0.00	0.97	0.96	0.97	0.96
18	1.00	0.00	0.97	0.97	0.98	0.97

Table 1: True positive rates (TPR) and true negative rates (TNR) for identifying certificate earners with different interaction representations.

We use 5-fold cross-validation over the 8.02x's 18 week duration as our primary heuristic. Table 1 shows the average scores broken down into true positive rates (TPR) for identifying certificate earners and true negative rates (TNR)for identifying non-certificate earners. Comparing both metrics illuminates any asymmetries in performance due to class imbalance [1].

Based on Table 1, binary indicators failed to accurately identify certificate earners, labeling the entire sample space as non-certificate earners. Even with Different Error Costs (DEC), there was not enough of a distinction between non-certificate and certificate earners, which is likely a vestige from some non-certificate students quickly scanning all of the course's content. Interaction counts and time spent performed better at identifying certificate earners, as these two representations were not as susceptible to such extensive exploration. Time spent had a slight advantage over interaction counts, making our choice for the base representation of students for training LDA.

Identifying the Number of Use Cases Through Log Perplexity

Using the time spent on modules representation, 5-fold cross-validation of log-perplexity per interaction is displayed in Figure 5. The optimal number of use cases appeared to be around 50, however, it is unclear from cross-validation alone how much of effect such a large number of use cases has on our ability to interpret the model.

Determining the right balance between predictive performance and interpretability is currently an open issue in probabilistic topic modeling [2]. Although there has been some

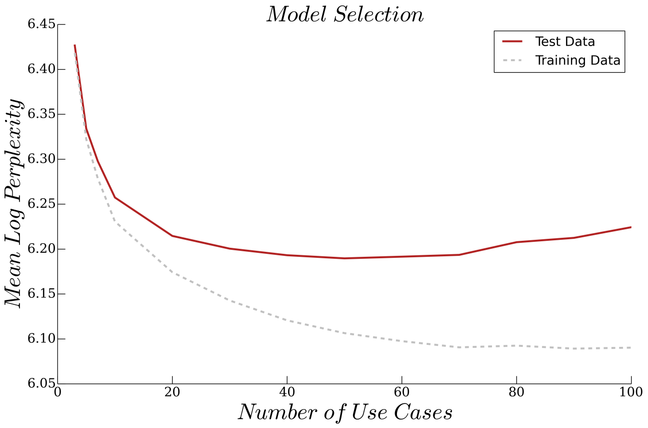


Figure 5: 5-fold log perplexity for a varying number of use cases.

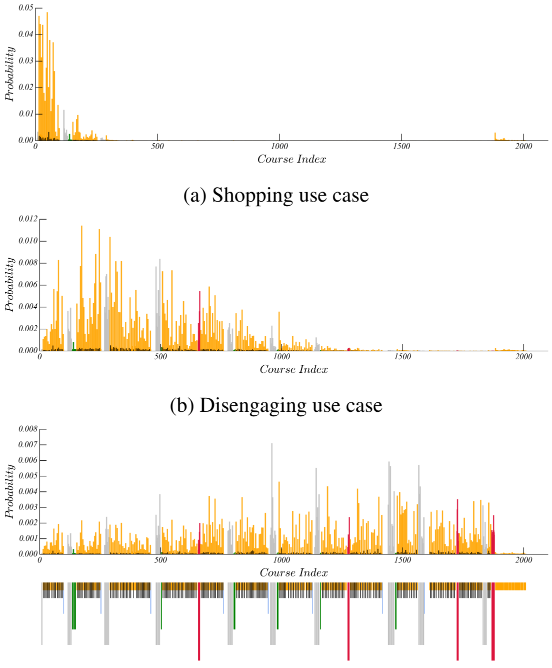
work that tries to quantify interpretability [6], our vocabulary of course modules is only understood by a small set of individuals, making it difficult for us to apply those strategies here. Hence, in the next section we chose to visually explore the how use cases vary and separate as the number of use cases increases.

Probabilistic Use Cases

This section illustrates the descriptive power of probabilistic use cases by plotting their probability distributions according to the course structure. With the 3-use case model as a baseline, we describe the resulting behavioral patterns. Subsequently, we investigate how these use cases evolved over the course's duration and subdivide as the number of use cases is increased.

Figure 6 shows the probability distributions of the 3-use model after all 18 weeks of 8.02x. Each probability distribution is color-coded according to the course structure visual aid appearing as the lower most x-axis. The visual aid is simply a rotation of Fig. 1, where color indicates type of resources, and the length of each vertical bar is the weight toward final grade. In order to ensure consistency, all figures in this section use the same visual aid in conveying course structure within each probability distribution.

Each of the presented use cases in Figure 6 illuminates a distinct behavioral patterns in 8.02x. The use case in Figure 6a concentrated the majority of its probability on videos from the first week of the courses. This skewed distribution resulted from the large population of registrants that only watched the videos at the beginning of the course before stopping activity - we hypothesize that these users were simply "shopping", although many other possibilities exist. Figure 6b captures users who actively participated in the course yet disengaged midway through. Finally, the distribution in Figure 6c remains roughly uniform throughout the course, signifying significant engagement with the majority of the course material. Together these 3 use cases represent intuitive groups (shopping, disengaging, and completing) for students based on their interactions with the courseware.



(a) Shopping use case

(b) Disengaging use case

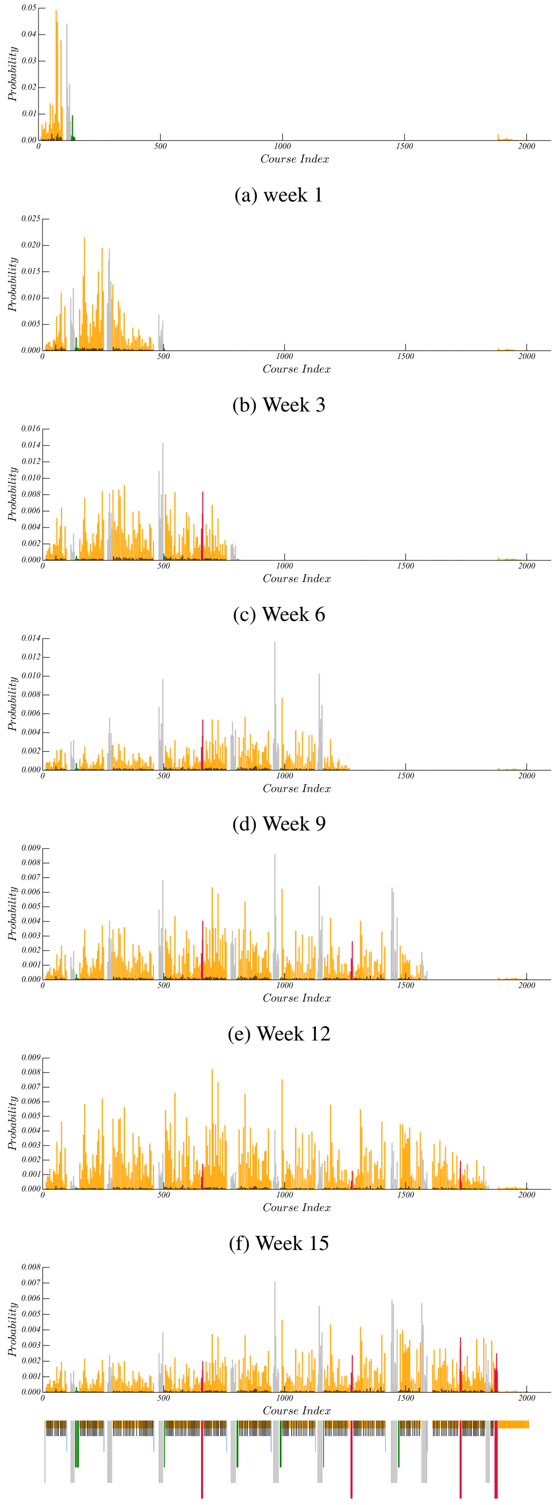
(c) Completing use case

Figure 6: Probability distributions from a 3-Use Case Model of 8.02x over all released content during the 18 week running. A course structure visual aid – similar to that found in Figure 1 – is below the lowermost probability distribution. All probability distributions are coded according to this visual aid: color – the type of resource, width – density of resources, and height – weight toward final grade (height of bars).

These three use cases groups were evident from the very beginning of the course. The shopping use cases remained virtually unchanged after the first two weeks of the course, while the disengaging and completing slowly spread their distributes out, as new material was released. Figures for each use-case per week will be made available online. Unfortunately, due to space constraints, we only show the evolution of the "completing" use case in roughly 3-week intervals over the 18-week course – see Figure 7.

For the students in this cohort engaged with material as soon as it was released, following the instructor's intentions. The disengaging use case had a similar, although delayed, progression to the completing use cases, where students increasingly lagged behind as new material was released. Overall the behavioral patterns captured in Figure 6 remained well-defined throughout the course, defining consistent archetypes for students.

Increasing the number of use cases breaks these archetypes into additional behavior patterns based on the types of materials accessed and the percentage of the course utilized. Figure 8 depicts the 10-use case model trained on all 18 weeks of 8.02x. Users that failed to make it to the end of the course are represented by use cases in Figures 8a, 8b, 8c, and 8d.



(a) week 1

(b) Week 3

(c) Week 6

(d) Week 9

(e) Week 12

(f) Week 15

(g) Week 18

Figure 7: The evolution of the completing use case from the 3-Use Case model (Figure 6c) over the 18 weeks of 8.02x. Figure 7g contains the course structure visual aid.

The shopping use case (see Figure 6a) reemerges most clearly in Figure 8a. Figure 8b potentially illuminates a shopping variant, where users are attempting solely the first problem set. Figures 8c and 8d resemble the disengaging use case in Figure 6b, highlighting potential inflection points in the course. The remaining 6 use cases embody the completing use case, as they separate their probability distributions across the course. Going from Figure 8e to Figure 8j there is a clear shift in probability from videos to assessments. Such separation indicts the degree to which student depended on videos, ranging from users that primary audited the class to potential experts that attempted the problem sets and exams with little instruction. Therefore, we get higher granularity into the behavioral trends with the course by varying the number of use cases.

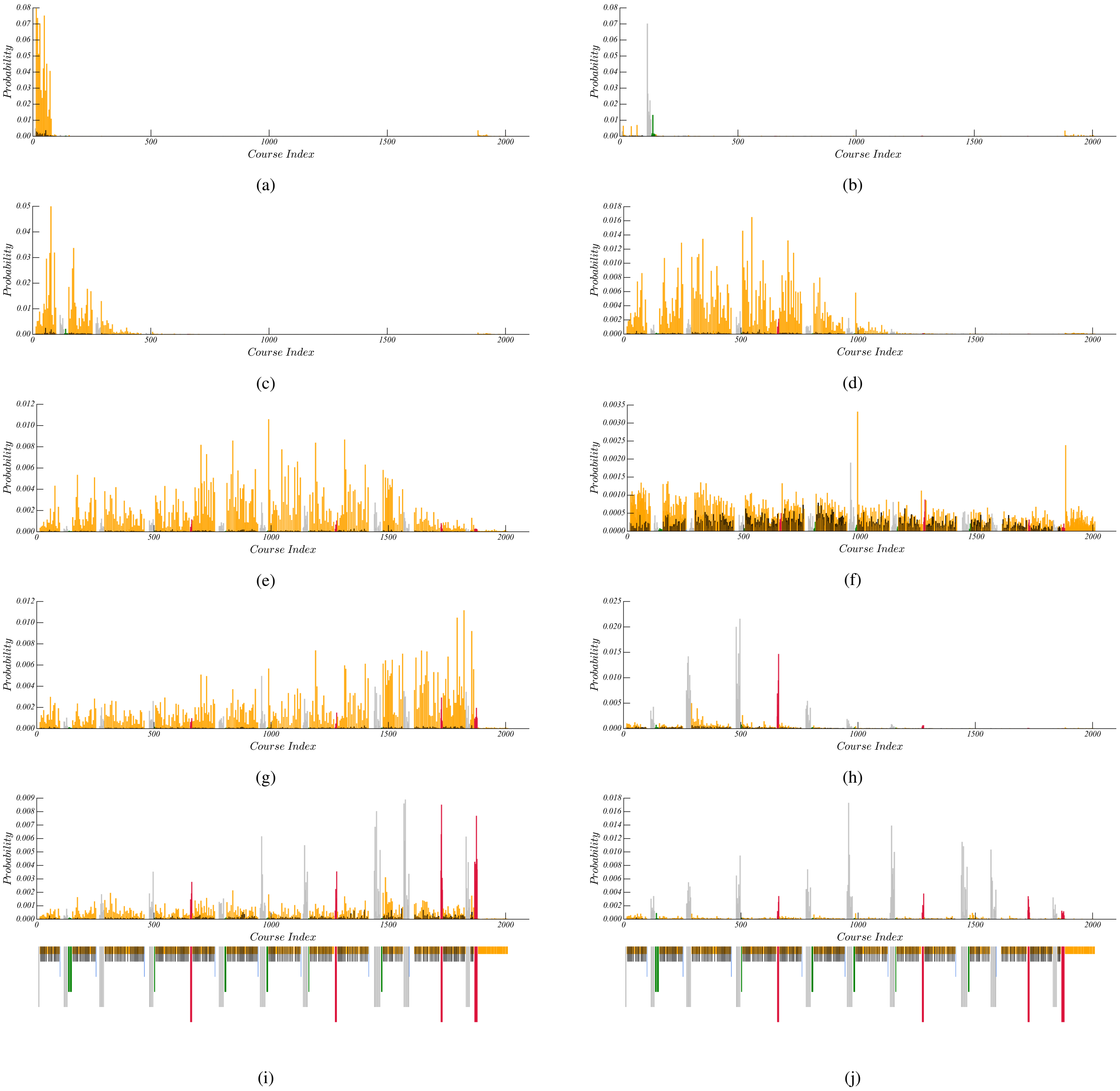
Predicting Certification

By substituting in students' use case proportions, we effectively reduce the dimensionality of the data from thousands of resources to a small number of use cases. This potentially allows for more accurate predictions of user outcomes. Through 5-fold cross validation, we test this hypothesis on weekly basis in 8.02x, using certification as our outcome of choice. Table 2 presents the overall accuracy rates (ACC), true positive rates (TPR), and true negative rates (TNR) for 3, 5, 10, and 50-use case models. Despite the initial drop in TNR in comparison to base representation of time spent in Table 1, the use case formulations yield much higher TPR, providing balanced prediction performance between certificate and non-certificate earners. Moreover, as the number of use cases increases, both the TNR and TPR increase. At the peak of 50 use cases, a SVM classifier with Different Error Costs (DEC) achieves 0.81±0.01 accuracy at predicting certification with just one week of data. Even with only 3 use cases the, prediction accuracy is still at 0.71±0.01 with only one week of data.

DISCUSSION

Applying LDA to 8.02x provides a data-driven approach to understanding student behavior that transforms massive amounts of statistical information into a set of use cases that are more easily characterized and communicated. Investigating the probability distributions associated with each use case can help researchers distinguish archetypes such as auditors, completers, and even experts. The true descriptive power of LDA, nevertheless, comes from its mixed-membership model. Because students have their own proportions for each use case, important differences between users are preserved, which is critical in prediction.

Despite the preserved statistical information, the implementation of LDA in this paper involves two assumptions regarding the student data. First, LDA assumes that the order of the interactions does not matter when determining the use cases. The graphical model in Figure 4 indicates this assumption, as permutations of interactions do not affect the overall likelihood of the model. However, the order of student interactions can encode valuable information about behavioral patterns. For example, consider playing a video in a lecture sequence and answering the question that follows it. Answering the



(a)

(b)

(c)

(d)

(e)

(f)

(g)

(h)

(i)

(j)

Figure 8: Probability distributions for each use case in a 10-Use Case Model trained on all 18 weeks of logs from 8.02x. In contrast to the 3-Use Case Model, the 10-Use Case model provides higher granularity into disengaged and engaged behavior trends. Figure 8i and Figure 8j contain the course structure visual aid.

	3-use case model			5-use case model			10-use case model			50-use case model		
Week	ACC	TNR	TPR	ACC	TNR	TPR	ACC	TNR	TPR	ACC	TNR	TPR
1	0.71±0.01	0.70	0.79	0.77±0.01	0.77	0.76	0.81±0.01	0.81	0.75	0.81±0.01	0.81	0.74
2	0.79±0.01	0.78	0.93	0.83±0.01	0.82	0.90	0.83±0.02	0.82	0.89	0.85±0.02	0.85	0.90
3	0.87±0.02	0.86	0.96	0.84±0.02	0.83	0.96	0.88±0.02	0.87	0.96	0.90±0.02	0.90	0.94
4	0.90±0.01	0.89	0.97	0.91±0.02	0.90	0.97	0.91±0.02	0.90	0.97	0.93±0.02	0.93	0.95
5	0.87±0.02	0.86	0.98	0.91±0.02	0.91	0.98	0.91±0.02	0.91	0.96	0.93±0.02	0.93	0.96
6	0.90±0.02	0.90	0.99	0.91±0.02	0.90	0.99	0.92±0.02	0.91	0.98	0.94±0.02	0.94	0.98
7	0.92±0.02	0.91	0.99	0.91±0.02	0.90	0.99	0.92±0.02	0.92	0.98	0.95±0.02	0.95	0.97
8	0.92±0.02	0.91	0.99	0.94±0.02	0.94	0.99	0.94±0.01	0.93	0.99	0.96±0.02	0.96	0.97
9	0.94±0.01	0.93	0.99	0.95±0.01	0.95	0.98	0.94±0.01	0.94	0.99	0.96±0.01	0.96	0.97
10	0.93±0.02	0.93	0.99	0.94±0.02	0.93	1.00	0.96±0.01	0.96	0.98	0.97±0.01	0.97	0.97
11	0.93±0.02	0.93	1.00	0.95±0.01	0.95	1.00	0.96±0.01	0.96	0.99	0.97±0.01	0.97	0.98
12	0.93±0.02	0.93	1.00	0.93±0.02	0.93	0.99	0.96±0.01	0.96	0.99	0.98±0.01	0.98	0.97
13	0.92±0.02	0.91	0.99	0.95±0.01	0.95	0.99	0.97±0.01	0.97	0.99	0.98±0.01	0.98	0.98
14	0.96±0.01	0.95	0.97	0.97±0.01	0.97	0.99	0.97±0.01	0.97	0.99	0.98±0.01	0.98	0.98
15	0.92±0.02	0.92	0.99	0.95±0.01	0.95	0.99	0.96±0.01	0.96	0.99	0.99±0.01	0.99	0.98
16	0.96±0.01	0.96	1.00	0.95±0.01	0.94	1.00	0.97±0.01	0.97	0.99	0.99±0.01	0.99	0.98
17	0.96±0.01	0.95	1.00	0.97±0.01	0.97	0.98	0.97±0.01	0.97	0.99	0.98±0.01	0.98	0.98
18	0.96±0.01	0.96	1.00	0.96±0.01	0.96	1.00	0.97±0.01	0.97	0.99	0.99±0.00	0.99	0.98

Table 2: Overall accuracy rates (ACC), true positive rates (TPR), and true negative rates (TNR) for 3, 5, 10, and 50-use case models at predicting certification.

question before watching the video alludes to a very different behavior than the reverse. Rather than following the natural order of the course, a student might be trying to optimize their behavior to get through the material as quickly as possible. To relax this constraint, the work of Wallach [25] or Griffiths et al. [10] could be adapted for use case modeling.

The second assumption is that the ordering of the students does not matter. Because enrollment took place throughout the running of 8.02x, this is not entirely true. The release and due dates for course content were spread across roughly 16 weeks, meaning students ultimately had different user experiences depending on date they enrolled. Such course features could potentially have a dramatic effect on behavior, which LDA does not currently capture.

Nevertheless, the application of LDA in this paper serves as a solid proof of concept. To truly validate the effectiveness of this approach, the methods needed to applied to a broad range of courses. As next steps, we are excited to explore how factors such as population size, course structure, or material effect the resulting use cases.

CONCLUSIONS

Our results show that LDA can be adapted in the context of user modeling in MOOCs. The descriptive power of this approach reveals a number of latent use-cases learned from data in the MITx on edX MOOC, 8.02x: Electricity and Magnetism. These use cases have shown distinct patterns of behavior, while preserving important statistical information for additional analysis. Perhaps most important, using only the first week of logs, probabilistic use cases can predict whether or not a student will earn a certificate with 0.81±0.01 accuracy.

Beyond research, it is our hope that this may impact course content teams and platform developers. The probabilistic representation of use cases provide simple intuition about which course components are utilized, and potentially more complex modes related to student behavior. The mixed-membership representation of students offered by LDA also has the potential to facilitate similarity queries between students on the basis of their behavior. From a platform perspective, these queries could in turn serve as the basis for intervention studies of specific cohorts. LDA adapted for user modeling provides key insights into behavior via a data-driven approach that could potentially form a foundation for adaptive design in large-scale applications.

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