style - fix broken quotes (use `` for opening quotes) and avoid contractions (let's -> let us)

Adaptive Teaching: Learning to Teach

by

there are a lots of issues with you putting too many commas and commas in weird places. I don't have time to point out all the instances, so please get help from a friend to fix the commas in the near-final version

Aazim Lakhani
Bachelor of Computer Engineering, Mumbai University, Mumbai, 2009

A Project Submitted in Partial Fulfillment of the
Requirements for the Degree of

MASTER OF SCIENCE

in the Department of Computer Science

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ABSTRACT

Traditional approaches to teaching were not designed to address individual students needs. We propose a new way of teaching, one that personalizes the learning path for each student. We frame this use case, as a contextual multi-armed bandit (CMAB) problem, a sequential decision-making setting in which the agent must pull an arm based on context to maximize rewards. We customize a contextual bandit algorithm for adaptive teaching to present the best way to teach a topic, based on contextual information about the student and the topic the student is trying to learn. To streamline learning we add an additional feature, which would allow our algorithm to skip topics that a student is unlikely to learn. We evaluate our algorithm, over a synthesized unbiased heterogeneous dataset to show that our baseline learning algorithm can maximize rewards to achieve results similar to an omniscient policy.

Contents

List of Tables

List of Figures

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Dr. Nishant Mehta for his dedication, commitment and insights, without which I would not have been able to overcome the gaps I could not see.

Almighty One for giving me the courage, belief and strength to pursue pursue my ideas

Mom for her blessings and prayers.

DEDICATION

I dedicate this project to my family, to whom i owe both the joy and pain of growing up.

Chapter 1

Introduction

The quest for a fully personalized learning experience began with the development of intelligent tutoring systems (ITSs) [5, 12, 26, 28]. However, till date, ITSs are primarily rules-based, which requires domain experts to consider every possible learning scenario that students can encounter and then manually specify the corresponding learning actions in each case. This approach is not scalable since it is both labor-intensive and domain-specific [14].

Machine learning-based personalized learning systems have shown great promise in reaching beyond ITS to scale to large numbers of courses and students. These systems automatically create personalized learning actions, for each individual student to maximize their learning. Examples of actions include reading a textbook section, watching a lecture video, interacting with a simulation or lab, solving a practice question, etc. Instead of domain-specific rules, machine learning algorithms are used to select actions automatically by analyzing the data students generate as they interact with learning resources[14].

The goal of this project is to design a learning algorithm, which could adapt based on students feedback to help them learn effectively.

1.1 Use Case

There is no universal best way to explain a topic. The best way is subjective to every student. Unless we explore different ways to teach a topic, we cannot find a policy, which would help map different students to explanations conducive for them. Once, we have such a policy we can use it to teach students effectively. **This is**

the exploration-exploitation dilemma in which we have to find a trade-off between two competing goals: maximizing students satisfaction in the long run, while exploring uncertainties in students preferences [2]. For example, an adaptive teaching system should present different explanations knowing students preferences on learning. However, unless we try different ways of teaching, it is not possible to say with certainty whether or not an explanation would help a student learn effectively. We use the term adaptive teaching to avoid mixing it with adaptive learning used in machine learning literature. In the education domain, these terms are used interchangeably.

We represent this use case as a contextual bandits problem. We use contextual information about the student, such as their preferences to learn through *visual, text, demo-based, practical, activity-based, step-by-step, lecture, audio-based explanations, as well as, self-evaluation and pre-assessment of students.* We also use contextual information about the contents used to teach a topic, by rating them in terms of *ease of understanding, simplicity, intuitiveness, depth in teaching, conciseness, thoroughness, ratings, abstractness, hands-on, experimental.* A **content item or arms are different actions or ways a topic can be taught**. The reward would be the students feedback to confirm their understanding of the topic they are trying to learn. The feedback could be in the form of *quizzes (e.g: ask a question), interactions, (e.g: Highlight content, notes, clicks) task (e.g: find an application of reinforcement learning in real life*). **By pulling an arm, we obtain a reward, drawn from some unknown distribution determined by the selected content item and the context. Our goal is to maximize the total cumulative reward**.

Let's make this more concrete by mapping this use case to teaching a class. In any school, a course comprises of multiple topics. However, now instead of a single way of teaching everyone, there would now be multiple ways to teach. These different ways of teaching are referred to as content items. Students give their feedback on the presented content. Behind the scenes, our learning algorithm, which takes information about the student *(also referred to as student context)*, topic, content items*(also referred to as content context)* to find the best way to teach a student. This project extends the most cited contextual bandit learning algorithm, LinUCB (Linear Upper Confidence Bound) [16] to enhance it for our use case.

1.2 Motivation

The primary and perennial problem in education is the overwhelming challenge of teachers being responsible to accomplish learning mastery among a demographically diverse set of students. [21]. In traditional classrooms, learning has largely remained a "one-size-fits-all" experience in which the teacher selects a single learning action for all students in their class, regardless of their diversity in needs, prior knowledge, skills, learning styles, and backgrounds. It's not feasible for teachers to ensure their explanations can cater to all students. Hence, there is a need for a system which could personalize teaching for students to help them learn effectively, as well as, increase course engagement and progression.

'Such systems / Such a system' is repetitive...Also I do not think each sentence should be a separate paragraph.

Such systems would be adaptive, recognize different levels of prior knowledge among students, as well as course progression based on students skill and feedback from learning to decrease faculty load in teaching to remediation to teaching and facilitating.

Such systems would conform to individual students learning patterns ~~as against~~ ~~to~~ students having to conform to the way of teaching.

instead of

Such a system would provide timely and comprehensive data-driven feedback, to recognize potential challenges that students might come across as the course progresses.

1.3 Contribution

We suggest a novel baseline algorithm, for our proposed adaptive teaching methodology, which learns from students and contents for each topic to create a personalized learning path, which adapts dynamically, based on student's feedback and learning preferences.

I don't think you know this. You are speculating here, right? You have to be careful in being accurate since this is a scientific document. You can soften the claim by saying "which is meant to increase student retention"

We also provide a skip feature to keep students engaged which increases student retention, as well as provides feedback to teachers by recognizing the challenges faced by a student, early in the course.

unclear; are you saying the skip feature "provides feedback"? or are you saying *another* feature is providing of feedback. Please rephrase/ reorganize the sentence to clarify

Our online learning algorithm gives close to optimal results, over a synthesized unbiased heterogeneous dataset.

what do you mean by unbiased here? The notion of an unbiased dataset is not something I've heard of before

1.4 Organization

Chapter 1 provided a brief overview of a novel adaptive teaching system, the need for it and our contribution.

Organize this into a paragraph, and make it flow. Don't just give a list of stuff. Tie together this collection of statements

Chapter 2 gives a brief description of the online sequential decision-making setting, we use to create our algorithm.

Chapter 3 describes prior work related to our use case.

Chapter 4 contains the algorithm created for adaptive teaching, along with the skip feature.

Chapter 5 details the experimental setup, dataset synthesized for these experiments and evaluation strategy.

Chapter 6 presents the results of our experiments and evaluates the performance of our algorithm.

Chapter 7 concludes this project by summarizing the contributions and outlines avenues for future work.

Chapter 2

Preliminaries

To understand our work, there are some ~~recommended~~ pre-requisites that should be understood before proceeding. Below are the key concepts.

2.1 Multi-Armed Bandits

What is "It"? You never explain this.

Remember that MAB problems include both adversarial problems and stochastic problems. Please re-phrase to say that you are discussing the stochastic MAB problem

It is a problem setting, where an agent needs to make a sequence of decisions in time $1, 2, ..., T$. At each time t the agent is given a set of K arms to choose and has to decide which arm to pull. After pulling an arm, it receives a reward for that arm, and the rewards of other arms are unknown. It's a stochastic setting where the reward of an arm is sampled from some unknown distribution. [29]

"from some unknown, arm-dependent distribution", to make clear that each arm has its own distribution

Personalized recommender systems recommend ~~the~~ items (e.g., movies, news articles) to the users based on their predicted individual interests on these items. The users response helps the system improve their prediction[?]. However, the response to any particular item can only be available after these items are recommended. If an item is never shown to the users, the recommender systems cannot collect the response on these items. Such problems can be naturally modeled as a contextual bandit problem [27]

2.2 Contextual Bandits

In the theory of sequential decision-making, contextual bandit problems [25] occupy a middle ground between multi-armed bandit problems [6] and full-blown reinforcement learning (usually modeled using Markov decision processes along with discounted or

average reward optimality criteria) [24]. Unlike bandit algorithms, which cannot use any side-information or context, contextual bandit algorithms can learn to map the context into appropriate actions. However, contextual bandits do not consider the impact of actions on the evolution of future contexts. Nevertheless, in many practical domains where the impact of the learners action on future contexts is limited, contextual bandit algorithms have shown great promise. Examples include web advertising [1] and news article selection on web portals [16] [11]

Please explain the basic contextual MAB problem first. Then, show how your setting can be modeled as one of these problems. **Please send me an updated version once you have the general contextual MAB problem explained**

We can formulate adaptive teaching use case to a contextual-bandit algorithm A which proceeds in discrete trials $t = 1, 2, 3, ...$ In trial t:

1. The algorithm observes the student context x_s and a set A_t of content items together with their feature vectors x_c for $a \epsilon A_t$. X_t summarizes information of both the student x_s and content item x_c, and will be referred to as the context.

the reader might get confused if you switch between 'reward' and 'payoff' randomly throughout the document

2. Based on observed payoffs in previous trials, A chooses an arm $a_t \epsilon A_t$, and received payoff r_t for arm a_t whose expectation depends on both the context X_t and the arm a_t.

here and throughout, don't use \epsilon. Use \in. This will make your "is an element of" symbol render correctly

3. The algorithm then improves its content item selection strategy with the new observation, (x_t, a_t, r_t). It is important to emphasize here that no feedback namely, payoff r_t is observed for unchosen arms $a \neq a_t$

At time t, side information, also known as the context is observed. In our problem setting, context would be information about the student and contents. The content item which has the highest expected reward may be different for each context. [16]

2.3 Upper Confidence Bound (UCB)

A perpetual challenge in bandit algorithms is to find the right balance between exploration and exploitation (Section 1.1). Upper Confidence Bound (UCB) comprises of a family of algorithms which try to find the best trade-off between exploration and exploitation. It is based on the principle of *optimism in the face of uncertainty*, which is to choose actions as if the environment is as nice as possible. The intuitive reason that this works is that when acting optimistically one of two things happens. Either the optimism was justified, in which case the learner is acting optimally, or the optimism was not justified. In the latter case, the agent takes some action that they believed might give a large reward when in fact it does not. If this happens

There are a lot of these wrong with this statement. Maybe it will be clearer if you just provide a quick example in the case of ordinary UCB with no context?
Some of the issues: UCB uses the sample mean (empirical mean, not the 'mean', where 'mean' always means the actual unknown mean of the random variable). Also, a confidence interval is already an interval centered around the empirical mean. So, if you add the empirical mean to this, you would end up getting the wrong thing (you would have shifted it, whereas it was already in the right place!). Also, UCB is one-sided. It does not care about the part of the confidence interval that is below the empirical mean.

sufficiently often, then the learner will learn what is the true payoff of this action and not choose it in the future [15]. UCB algorithms are defined by the mean and the confidence interval around the mean. These two terms are added together to give an upper confidence bound for an arm.

2.4 Linear Upper Confidence Bound (LinUCB)

LinUCB is a way to apply UCB to a more general contextual bandits setting, where the mean is given by $\widehat{\theta}_a^T x_{t,a}$ and the confidence interval is given as $\sqrt{x_{t,a}^T A_a^{-1} x_{t,a}}$ It defines a parameter α to scale the confidence interval. A higher value of α implies a higher confidence interval which means the algorithm would take more trials to explore, before it begins exploiting. **The expected estimated payoff for an arm at trial t is given as** $p_{t,a} = \widehat{\theta}_a^T x_{t,a} + \alpha\sqrt{x_{t,a}^T A_a^{-1} x_{t,a}}$ [16]

does the reader know what A_a is here? I don' t think you have explained what this is

I find the description of LinUCB as really terse and I think it will leave the reader confused. This is an ideal time to give your own detailed explanation of how it works, to help inform the novice reader. You cannot assume, e.g., that George knows about LinUCB. Think about whether he will have a clear picture into it after reading Section 2.4.

Chapter 3

Related Work

I have not looked at the reference [14], but you seem to refer to it a lot, and I wonder if it is very similar to what you are doing. Therefore, in this Related Work section, you also need to contrast your approach to theirs

Our use case could also be formulated using the partially observed Markov decision process (POMDP) framework. POMDPs utilize models on the students latent knowledge states and their transitions to learn an action selection policy that maximizes reward received in the possibly distant future (long-term learning outcome). Previous work applying POMDPs to personalized learning has achieved some degree of success. However, learning a personalized learning schedule using a POMDP is greatly complicated by the curse of dimensionality. The solution quickly becomes intractable as the dimensions of the state and action spaces grow. Consequently, POMDPs have made only a limited impact in large-scale personalized learning applications involving large numbers of students and learning actions. [14]

citations always go before the period. Like, "and learning actions [14]." Change here and throughout

A more scalable approach to personalized learning is to learn a policy, which maps contexts to actions using the multi-armed bandits (MAB) framework, which is more suitable for optimizing students success. The simplicity of the MAB framework makes it more practical than the POMDP framework in real-world educational applications[14]

The work in [17] applies a MAB algorithm to educational games in order to trade off scientific discovery (learning about the effect of each learning resource) and student learning. Their approach is context-free and thus not ideally suited for applications with significant variation among the knowledge states of individual students. Indeed, it can be seen as a special case of our work when there is no context information available. The work in [19] collects high-dimensional student - computer interaction features as they play an educational game and uses them to search for a good teaching policy. [14]

Are you sure this is true? Have you read what they declare the goal of their paper to be? See the last paragraph of Section 3 of [17]. I do not think your claim is fair, since their objective is different

The works in [8, 13] both use a form of expert knowledge to learn a teaching

policy. The approach of [8], in particular, uses expert knowledge to narrow down the set of possible actions a student can take. Our approach, in contrast, requires no expert knowledge and is fully data-driven. [14]

The work in [23] found that various student response models, including knowledge tracing (KT) [9], Item Response Theory (IRT) models [18, 22, 4], additive factor models (AFM) [7], and performance factor models (PFM) [10] can have similar predictive performance yet lead to very different teaching policies. While these results are ~~indeed~~ interesting, we emphasize that the focus of the current work is to develop policy learning algorithms rather than comparing student models. [14]

Chapter 4

Algorithm

This chapter presents the algorithm created for the adaptive teaching system. We first present the basic version of the algorithm (Section 4.1). We then explain the skip feature (Section 4.2), which could streamline learning.

The algorithm used is an extension of upper confidence bound (UCB)-based algorithms [3]. These algorithms maintain estimates of the expected reward of each arm together with confidence intervals around these estimates. It iteratively updates them after each new pull and its corresponding reward is observed. They then pull the arm with the highest UCB, which is equal to the sample mean among the rewards observed plus the width of the confidence interval. [14]. In this project, we are using the most cited contextual bandit algorithm, namely LinUCB (Section 2.4)

Before we dive in, it is important to note, that to better understand the algorithm, I have divided the explanation into two halves. *The first half, explains the overall flow without skipping, whereas the second explains in-depth the function calls made in the first half along with skipping.* I would be using bandit terminology to explain. **Arm** corresponds to a content item. **Payoff** refers to the estimated reward computed by the algorithm. **Round** refers to selecting a content item and getting student feedback for the content item.

Before we proceed to the algorithm, below are the notations, you will come across.

Symbol	Meaning
α	Parameter to adjust Confidence bound.
C	Confidence threshold to skip.
$\mathbf{x_s}$	Student context vector.
x_c	Content items context.
$\mathbf{x_t}$	Context vector at round t.
X_t / X_t^i	Context at round t. It combines $\mathbf{x_s}$ and all available x_c for topic i.
X_t^{i+1}	Context at round t. It combines $\mathbf{x_s}$ and all available x_c^{i+1} for topic $i+1$.
x_c^{i+1}	Content items contexts for topic $i+1$.
a	An arm a for topic i.
a'	An arm a' for topic $i+1$.
A_t	Arms available at round t.
$A_{t'}^{i+1}$	Arms available for topic $i+1$ at round t'.
a_t^{i+1}	Arm a for topic $i+1$ at round t.
t	Current round t.
t'	Possible next round t'.
T	Total number of rounds.
i	Topic being taught.
$i+1$	Next Topic in the sequence.
$p_{t,a}$	Expected payoff from arm a at round t.
$p_{t,a}^i$	Expected payoff from arm a at round t for topic i.
$p_{t',a'}^{i+1}$	Expected payoff from arm a' at round t' for next topic $i+1$.
X	Input features for skip classifier.
Y	Label to train the skip classifier.

Table 4.1: Important Algorithmic Notations

Note

- We're always on the current topic i, unless we explicitly specify next topic $i+1$.
- All vectors are **bold** faced lower cased.
- All sets are upper cased.

Algorithm 1 Teach with LinUCB

Hyper Parameters : $\alpha \in \mathbb{R}_+$

C : Confidence threshold to skip

Inputs : Student context $\mathbf{x_s}$ and content context x_c of available arms $a \in A_t$ for topic i at round t

Prepare context $X_t = \begin{pmatrix} \mathbf{x_s} \\ x_c \end{pmatrix}$

skip-enabled $\leftarrow$ False

while $A_t \neq \emptyset$ **do**

  a_t^i , $p_{t,a}^i \leftarrow$ EXPECTED-PAYOFF(X_t,A_t)

  skip-decision , $p_{t',a'}^{i+1} \leftarrow$ SKIPTOPIC($\mathbf{x_s}$, $p_{t,a}^i$, i)

  if skip-decision , skip-enabled is True **then**

    Move to next topic $i \leftarrow i + 1$

    break

  else

    Pull arm a_t and observe reward r_t

    $A_{a_t} \leftarrow A_{a_t} + \mathbf{x_{t,a_t}} \mathbf{x_{t,a_t}^T}$

    $\boldsymbol{b_{a_t}} \leftarrow \boldsymbol{b_{a_t}} + r_t \mathbf{x_{t,a_t}}$

    label $\leftarrow$ SETLABEL(r_t)

    TRAIN($\mathbf{x_s}$, $p_{t,a}^i$, $p_{t',a'}^{i+1}$,label)

    $t \leftarrow t + 1$

  if $r_t \neq 1$ **then**

    Remove $a_t \in A_t$

    skip-enabled $\leftarrow$ True

  else

    Move to next topic : $i \leftarrow i + 1$

    break

4.1 Basic Version

The basic version is without skipping. It explains the basic flow of the algorithm. The next section, explains the functions used along with skipping.

The algorithm requires two hyper-parameters to be configured. The first one is α which decides the confidence interval (Section 2.4). The second hyper-parameter is the confidence threshold C which decides confidence threshold that must be exceeded to skip a topic. Skipping is a feature to help reduce students struggling with topics and are unlikely to learn from remaining content items. It is meant to streamline learning. This helps teachers recognize topics to be addressed in class.

We now explain how LinUCB (Section 2.4) helps the algorithm decide an arm to pull. Before we recommend a content item to a student, we need to prepare context X_t for the round t. It is prepared by combining the student context $\mathbf{x_s}$ with content items context x_c for the topic i being taught. With the context X_t and arms A_t, we use LinUCB to compute an upper confidence bound (UCB) for each arm and return an arm a_t^i with the maximum expected payoff $p_{t,a}^i$ which must be pulled for topic i at round t.

Assuming the classifier does not recommend skipping, a student is presented with the content item a_t for topic i. After being taught, the student sends a reward r_t to complete the round t. Now the round t is complete We update the parameters A_{a_t} , $\mathbf{b_{a_t}}$ of the pulled arm. We then use this reward r_t to train the skip classifier, to make better predictions in upcoming rounds. The features for the classifier comprise of students contextual information $\mathbf{x_s}$, expected payoff $p_{t,a}^i$ of pulling arm a in round t for topic i and the expected payoff $p_{t',a'}^{i+1}$ of pulling arm a' in round t' for topic $i+1$.

If no reward r_t was sent by the student $\mathbf{x_s}$, then it implies the student was unable to understand topic i. In which case, the algorithm removes the presented arm a_t and remains on the same topic i. However, if a reward r_t was sent, then the student is moved to the next topic $i+1$.

That completes the first half. The second half explains the functions briefly described in the first half.

4.2 Skipping

On line 6 (Section 4.1) of the algorithm, we get the expected payoff $p_{t,a}^i$ estimated on pulling the arm a_t^i for the current topic i. Now, to decide whether or not it should

function SkipTopic(x_s, $p^i_{t,a}$, i)
    Get next topic $i+1$ from topic i
    Get arms $A^{i+1}_{t'}$ and content context x^{i+1}_c for topic $i+1$
    Prepare context vector $X^{i+1}_{t'} = \begin{pmatrix} x_s \\ x^{i+1}_c \end{pmatrix}$
    $a^{i+1}_{t'}$, $p^{i+1}_{t',a'} \leftarrow$ EXPECTED-PAYOFF($X^{i+1}_{t'}$,$A^{i+1}_{t'}$)
    skip-decision $\leftarrow$ PREDICT(x_s, $p^i_{t,a}$, $p^{i+1}_{t',a'}$) to decide on skip
    return skip-decision , $p^{i+1}_{t',a'}$
function EXPECTED-PAYOFF(X_t,A_t)
    for $a \epsilon A_t$ **do**
        Get $x_{t,a} \epsilon X_t$
        if a is new **then**
            $A_a \leftarrow I_d$ (d-dimensional identify matrix)
            $\boldsymbol{b_a} \leftarrow 0_{d\times 1}$ (d-dimensional zero vector)
        $\widehat{\theta}_a \leftarrow A_a^{-1} b_a$
        $p_{t,a} \leftarrow \widehat{\theta}_a^T x_{t,a} + \alpha\sqrt{x_{t,a}^T A_a^{-1} x_{t,a}}$
    Choose arm $a_t = \arg\max_{a\epsilon A_t} p_{t,a}$ with ties broken arbitrarily
    return $a, argmax p_{t,a}$,
function PREDICT(x_s, $p^i_{t,a}$, $p^{i+1}_{t',a'}$)
    X $\leftarrow x_s$,i+1 , $p^i_{t,a}$, $p^{i+1}_{t',a'}$
    Y , confidence-score $\leftarrow$ Prediction from classifier
    if confidence-score <C **then**
        decision $\leftarrow 0$
    return decision , confidence-score
function TRAIN(x_s, $p^i_{t,a}$, $p^{i+1}_{t',a'}$, label)
    $X \leftarrow x_s, p^i_{t,a}, p^{i+1}_{t',a'}$, topic ,
    $Y \leftarrow$ label
    Train online SGD classifier
function SETLABEL(r_t)
    if r_t is 0 **then**
        label $\leftarrow 1$
    else
        label $\leftarrow 0$
    return label

remain on the same topic or move to the next topic, it calls the skip topic function.

The *SKIPTOPIC* function, takes the student context $\mathbf{x_s}$, the expected payoff $p^i_{t,a}$ for pulling arm a at round t for topic i and the current topic i. It uses the topic i to get a reference to the next topic $i+1$. Through the topic $i+1$ it gets content items $A^{i+1}_{t'}$ and context data x^{i+1}_c associated with it. After combining the contexts to prepare $X^{i+1}_{t'}$, it gets the maximum expected payoff $p^{i+1}_{t',a'}$ and the arm $a^{i+1}_{t'}$ by passing the context vector $X^{i+1}_{t'}$ and arms available for next topic $A^{i+1}_{t'}$. The expected payoff returns an arm with the maximum estimated payoff. Skip topic function then calls the skip classifier to predict a skip-decision for the student context $\mathbf{x_s}$, along with the expected payoff of current and next topic to make a prediction.

The *EXPECTED-PAY0FF* function takes the context X_t, along with the available arms A_t available at round t. After an arm a_t is initialized with parameters A_a, b_a , they are used to calculate the expected mean $\widehat{\theta}^T_a x_{t,a}$ and confidence bound $\sqrt{x^T_{t,a} A^{-1}_a x_{t,a}}$. The confidence bound is scaled by α. The expected mean and the scaled confidence bound are added to give the expected payoff $p_{t,a}$ for arm a at round t. It then finds an arm a with maximum expected payoff $p_{t,a}$ and returns it along with the arm a to be pulled.

The *PREDICT* function is used to predict whether the student should be moved to the next topic $i+1$ or should remain on the same topic i. It combines student context vector $\mathbf{x_s}$, the expected payoff $p^i_{t,a}$ of arm a at round t for topic i and the expected payoff $p^{i+1}_{t',a'}$ of arm a' at round t' for topic $i+1$ to prepare a feature vector X. Its then asks a prediction from the binary supervised online Support Vector classifier, with hinge loss to make a prediction Y and a confidence-score for its prediction. If the confidence-score is less than the confidence threshold, then set the *decision* variable is set to 0, which implies no skipping. This is because a confidence score lower than the threshold implies that the classifier is not confident enough about its prediction.

The *TRAIN* function is used to train the skip classifier to make better predictions. Similar to the predict function, it combines student context vector $\mathbf{x_s}$, the expected payoff $p^i_{t,a}$ of arm a at round t for topic i and the expected payoff $p^{i+1}_{t',a'}$ of arm a' at round t' for topic $i+1$ to prepare a feature vector X. It sets the *label* to the output Y. Together they train the skip classifier.

The *SETLABEL* function is used to set the *label* to train the skip classifier. If the reward r_t for round t is set to 0, then the *label* is set to 1, as it implies that since staying on the same topic did not give any reward, it would have been better to skip. If the reward r_t for round t is set to 1, then the *label* is set to 0, as it implies that

staying on the same topic was a good decision as it gave a reward. The set *label* is then returned.

Chapter 5

Experiments

This chapter explains the dataset (Section 5.1) used to evaluate the learning algorithm, along with the environmental setup (Section 5.2) in which it is used. The next section explains how we evaluate our algorithm (Section 5.3), in absence of pre-existing benchmarks, using an omniscient policy (Section 5.4). This is followed by sections which explain how the learning algorithm (Section 5.5) and the skip feature (Section 5.6) work with respect to the environment.

5.1 Dataset

Machine learning algorithms are data-driven. Due to the novelty of our approach, to the best of our knowledge, there is no similar dataset available. Hence, **we synthesized datasets to simulate students and courses taught using an adaptive teaching system.**

An honest attempt is made to synthesize an unbiased dataset representative of the heterogeneous students and content items. The contextual data is created from a uniform distribution U(0,1] sampled randomly to simulate the diverse nature of student preferences and content features.

5.1.1 Courses

We use the following courses for our experiments.

1. *Course 1 :* A course which comprises of 10 topics. Its taken by 50 students. There are a total of 119 content items for 10 topics. So on an average, there are

12 content items per topic. We use this course to find optimal hyper-parameters (α and C) for our learning algorithm.

2. *Course 2 :* A course which has 25 topics. Its taken by 100 students. There are 329 content items for 25 topics. So on an average, there are 13 content items per topic. We use this course for evaluation.

5.1.2 Context

We'll assume, there was a survey conducted among students, who were asked how should teaching be, to streamline learning? Students gave their preferences on a scale of 1 to 10, with 1 being least preferred and 10 being most preferred. These preferences were normalized.

Research has shown that students prefer to learn a certain way. Though there is no unanimous consensus, there is a fair bit of research and understanding on the needs of a student. The features we consider are by no means exhaustive, but representative subset of the main features. Below is a brief description of student and content related contextual information considered.

Student

I suggest using a table for this with 2 columns, one with things like Visual / Text / etc. and the other with the explanation of the thing in the first column. This long enumerated list is kind of awkward, and it would be nice if all of the student features were on the same page

1. *Visual (S_V)*: How much preference is given to visual explanations (video, short-film, movie-clip, vlogs)?

2. *Text (S_T)*: How much preference is given to written explanations (books, articles, blogs, research papers)?

3. *Demo-based (S_D)*: How much preference is given to live experiments to help understand a concept?

4. *Practical (S_P)*: How much preference is given to an explanation, followed by a demo of the topic, and enabling students to perform it?

5. *Step-by-step (S_S)*: How much preference is given to a guide to practice, try and understand a topic in a systematic way?

6. *Activity / Task-based (S_AT)*: How much preference is given to content items which are interactive and require students to participate?

7. *Lecture (S_L)*: How much preference is given to being passive and listen to an expert explain the topic?
8. *Audio (S_A)* : How much preference is given to audio explanations (podcasts, music) ?
9. *Self-evaluation (S_SE)* : Students self evaluation of their readiness, motivation, excitement for the course.
10. *Pre-assessment (S_PA)*: Teachers conduct a pre-assessment of the pre-requisites required for the course.

Content

Likewise, I suggest all content features going into a table instead

1. *Ease of understanding (C_E)* : How relatively easy is it to understand the content ?
2. *Simple / Intuition (C_I)*: Does the content provide a simple, intuitive understanding of the topic ?
3. *Surface / In-depth (C_ID)*: Does it provide a surface level or deep understanding of the topic ?
4. *Brief / Concise (C_C)* : Is it short, to the point or descriptive, verbose and elaborative, keeping in mind that learners have different levels of maintaining concentration and capacity to remember.
5. *Thorough (C_T)*: How well does the content item cover the topic ?
6. *Preference / Well reviewed / Well rated (C_R)* : How well rated is the explanation ?
7. *Theoretical / Abstract (C_A)*: How theoretical, abstract is the content item ?
8. *Practical / Hands on (C_P)* : Is it something that can be tried or experienced ?
9. *Experimental / Task-based (C_ETB)*: Does it require a task to be completed to fully understand it, like collaboration with other students or some research / findings ?

Apart from the above contextual data, there is a course which is taught. For our experiments, we consider a typical course which comprises of topics to be taught. These topics are labeled as *T_1, T_2 ... T_25.* For e.g: T_1 refers to the first topic of the course. Each topic has between 5 to 20 different content items. Each content is labeled in the format *C_topic-id_content-number*. For e.g: C_1_2 refers to the second content item for topic T_1.

We now have the required contextual information. Topics in the course are taught in a sequence outlined by the teacher. This allows them to control the course sequence.

An Example Data Point

Let's take an example data point to better understand the data.

Below (Figure 5.1) is a student context data point which shows a student preference. It tells us that this student prefers visual (S_V), text(S_T), demo-based(S_D) methods of learning, but does not prefer practical (S_P), activity-based(S_AT), and did not fare well in the pre-assessment(S_PA). Doesn't mind step-by-step(S_S), lectures(S_L) , audios(S_A) methods of learning and believes he/she is ready for the course (S_SE)

S_V	S_T	S_D	S_P	S_S	S_AT	S_L	S_A	S_SE	S_PA
0.87	0.82	0.88	0.36	0.6	0.06	0.66	0.56	0.66	0.07

Figure 5.1: Student Context Template

Below is a content context data point prepared for the course. This content item is thorough(C_T), practical(C_P), and experimentally sound(C_ETB), but not in-depth(C_ID),concise(C_C), and abstract(C_A). Its moderate in terms of understanding(C_E), intuitiveness(C_I) and has positive reviews(C_R)

	C_E	C_I	C_ID	C_C	C_T	C_R	C_A	C_P	C_ETB
C_1_1	0.45	0.72	0.31	0.05	0.91	0.75	0.06	0.88	0.97

Figure 5.2: Content Context Template

5.2 Environment

We run a simulation teaching courses to students with the omniscient policy and the learning algorithm, deciding the content item to be presented for each student. It an environment where there are several students taking the course at the same time. Both the omniscient policy and the learning algorithm work in online mode. The learning algorithm optimizes its parameters in each round to give better predictions.

5.3 Evaluation Strategy

Since there are no readily available benchmarks to compare our algorithm, we'll assume there exist an omniscient policy. This policy has optimal parameters to suggest the best arm to pull.

Hmm, you have this backwards. The omniscient policy depends on the underlying Bernoulli distributions, not vice versa. Please rephrase

We simulate the stochastic nature of student feedback as a Bernoulli distribution. The probability of success depends on the expected estimated payoff predicted by the omniscient policy. The algorithm tries to learn these optimal parameters by updating the parameters of the arm pulled after each round. The experiment conducted aims to find, whether our algorithm can optimize its parameters to match the cumulative reward of the omniscient policy.

It is here in Section 5.3 that you should explain how many rounds you run for. And, as I mention later, you must run both algorithms for the same number of rounds. If you do not do this, you need a really good explanation for why not, as every MAB paper does what I am suggesting you do.

5.4 Omniscient Policy

This policy knows all the probability distributions. It knows, every step of the way, the best decision based on its knowledge of the true distributions. It does not have to learn anything. It has optimal parameters θ^*, hence it is expected to maximize rewards.

does the omniscient policy ever skip? It seems that skipping is sometimes optimal, so it should, right? If you do not let the ominscient policy skip, then eventually your algorithm can do better than the omniscient policy, due to the additional power of skipping

This policy calculates the expected payoff of arm a which has optimized co-efficient vector $\theta_{t,a}$ and with context vector $x_{t,a}$ at round t by $E[r_{t,a}|\mathbf{x_{t,a}}] = x_{t,a}^T \theta^*_{\mathbf{t,a}}$

5.5 Learning Algorithm

The learning algorithm can adapt to several students at the same time to present a content item personalized for each student. For every topic a student is trying to learn, it gets the expected payoff for all available content items. It checks whether it

should skip to next topic or remain on the current topic. Skipping is activated only if the student gave no reward for a content item presented for the topic.

When a student is on a topic, the algorithm presents a content item that could maximize rewards. After working through the content item, the student shares feedback on the content item. If a reward is sent, then this implies that the student understood the concept and can be taken to the next topic. If no reward was sent, then the student may be presented with the next best content item for the same topic or could be moved to the next topic in the sequence.

Once the student has shared feedback on the content item, the data is sent to train the skip classifier, to make a better prediction in forthcoming rounds.

5.6 Skip Topics

The learning algorithm checks with skip topics to decide whether or not the content item should be presented for the current topic. Skip topics evaluate the estimated payoff for the current topic with the next topic in the course sequence.

It makes this decision using an online supervised learning, stochastic gradient descent classifier, with student context, along with the estimated payoff of the current and next topic to make a decision. The label for the classifier depends on the reward received for the topic. If a reward was sent, the label is set to 0, else set to 1. Thus, the classifier makes use of the feedback sent by students to recognize common topics and content items that students find difficult, so it could make a confident decision.

The aim to create skip topics feature is to streamline learning for students. If a student has been taught a topic once and was not satisfied with it, there is an option to skip to the next topic or explain the same topic with a different content item.

The skip classifier is a linear Support Vector Machine estimator with hinge loss. The estimator is a regularized linear model with stochastic gradient descent (SGD) learning. The gradient of the loss is estimated each sample at a time and the model is updated along the way with a decreasing learning rate. The regularizer is a penalty added to the loss function that shrinks model parameters towards the zero vector using squared Euclidean norm L2. [20]

Chapter 6

Results and Evaluation

where do you set the number of rounds (usually referred to as T in the MAB literature)?

This chapter presents results using the experimental set-up given in the previous chapter (Chapter **??**). We evaluate the learning algorithm with respect to the omniscient policy. Before evaluation, we need to first find optimal values for hyper-parameters α (Section 6.1) and confidence threshold C (Section 6.2). We then proceed to use these optimal values to evaluate the learning algorithm with and without the skip feature. (Section 6.3)

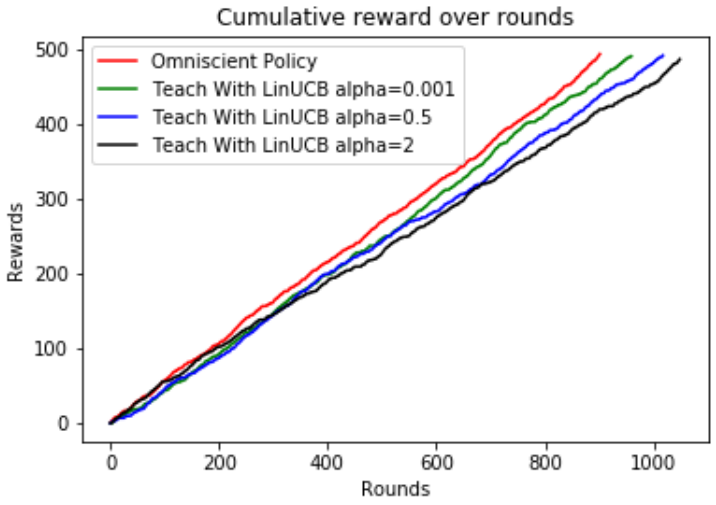
6.1 Confidence Interval α

Finding an optimal value for α is important to learn faster, as it scales the confidence interval of each content item. An optimal value would find the right balance between exploration and exploitation. A higher value of α would imply the learning algorithm takes more rounds exploring which can lead to sub-optimal results.

This parameter is configured for the learning algorithm and not the omniscient policy. We empirically evaluated an optimal value for α using course 1 (Section: 5.1.1). The graph (Figure 6.1) shows the cumulative reward for different values of α

The graph compares the omniscient policy with the learning algorithm for different values of α. It shows that the **cumulative reward is maximum when $\alpha = 0.001$** for the learning algorithm. On running repeated experiments, we found that any value of α between 0 to 0.5 gives optimal results. We would be using $\alpha = 0.001$ to evaluate the learning algorithm.

why do some curves stop before 1000 rounds? you should be running all algorithms for exactly the same number of rounds if you want to compare their cumulative reward



It is typical to plot the regret. In this case, you can plot, for each round t, the cumulative reward of the omniscient policy minus the cumulative reward of your policy. This is why you need to run both algorithms for the same number of rounds, as otherwise you cannot plot one curve substracted from the other

Figure 6.1: Cumulative Rewards For Values of α.

6.2 Confidence Threshold

This is a threshold on the confidence score the skip classifier should exceed, for its decision to be accepted. Skipping is enabled for a topic, only after a student gives no reward to a content item. The objective of the threshold is:

- To keep students engaged and skip topics they are unable to understand.
- Give teachers control on their preference to skipping.

We don't want the confidence threshold to be too high, as students might have to go through each content item, nor do we want it to be too low, such that students are taken to the next topic on the first occurrence of not understanding a topic. Hence, finding an optimal value for confidence threshold is important to have a good learning experience for students.

We evaluate the performance for different values of the confidence threshold over course 1 (Section: 5.1.1). Below are the results.

6.2.1 Without confidence threshold

We evaluated the skip classifier with no confidence threshold. Below is a confusion matrix of the results.

The classifier is measured on how well it helps the learning algorithm maximize cumulative reward. It shows that in 310 rounds, its decision helped increase rewards,

		Predictions		
		Stay (0)	Skip (1)	Total
Reward	0	181	40	221
	1	260	50	310
	Total	441	90	1062

Table 6.1: Confusion Matrix without Confidence Threshold

whereas in 221 rounds its decision gave no rewards. This shows us that about **58.38%** times, its decision helped increase the cumulative reward

6.2.2 With optimal confidence threshold

We evaluate the skip classifier with confidence threshold. We'll only consider data points where the skip classifier's decision was overridden as its confidence score was below the threshold. This would be when the skip classifier has suggested skipping to the next topic, but since the confidence score was below the threshold, the suggestion was ignored. This gives us the true measure of effectiveness for the confidence threshold.

We evaluated the classifier for different values of confidence threshold. For different threshold values performance ranged consistently between 55 - 58 %.We found the skip classifier performed most optimally when the confidence threshold is 10. The below table 6.2 shows the results.

		Predictions		
		Stay (0)	Skip (1)	Total
Reward	0	51	36	87
	1	70	55	125
	Total	121	91	424

Table 6.2: Confusion Matrix with Optimal Confidence Threshold

The above table shows, that **58.07 %** times, it made the correct decision. As the value of the confidence threshold was increased, the number of skips decreased. Table 6.3 shows the results for confidence threshold of 30.

		Predictions		
		Stay (0)	Skip (1)	Total
Reward	0	128	7	135
	1	178	9	187
	Total	306	16	644

Table 6.3: Confusion Matrix with Confidence Threshold of 30

Though our results do not justify the need for confidence threshold in terms of rewards for the learning algorithm, we believe that besides the reasons stated in section 5.6, it's also needed, as online learning algorithms suffer from *cold start* and their learning path is erratic before they stabilize.

6.3 Learning Algorithm

We now evaluate the learning algorithm with and without the skip feature.

6.3.1 Skipping Disabled

With skipping disabled the only way a student can move to the next topic is by understanding it or until all content items have failed to explain the student. This increases the number of rounds required per student to complete the course.

The figure 6.2 shows the cumulative reward of the learning algorithm with respect to the omniscient policy. The reward of the omniscient policy increases linearly, whereas that of the learning algorithm is sub-optimal. This is expected as it does not have optimal parameters from the beginning and has to learn in each round.

The cumulative reward graph shows that our learning algorithm is close to the optimal policy

6.3.2 Skipping Enabled

If a topic is not understood by a student then skipping is enabled. This doesn't directly imply the student would be taken to the next topic. For that to happen, the skip classifier should be confident beyond the confidence threshold to predict that it would be better to take the student to the next topic.

Skipping tells the learning algorithm to skip sub-optimal content items and instead move to content items that have a higher estimated payoff. This can lead to higher

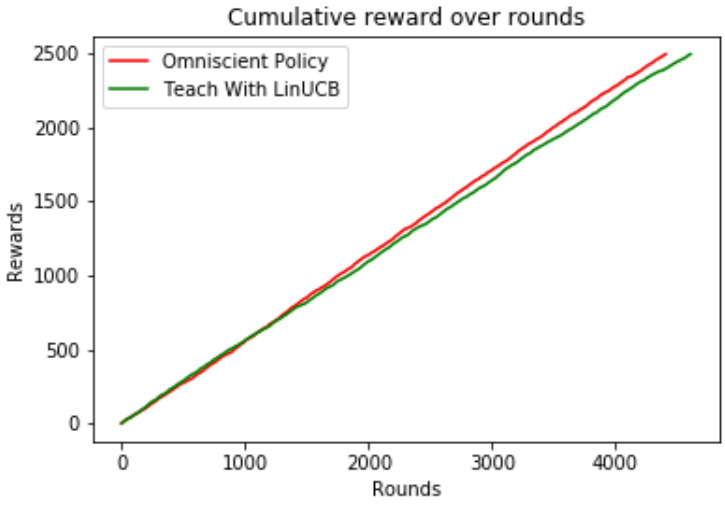


Figure 6.2: Compare Cumulative Rewards Without Skipping.

rewards. This also ensures we don't present content items, which is unlikely to help the student understand.

The figure 6.3 shows results of the learning algorithm with optimal confidence threshold $C = 10$ and confidence interval $\alpha = 0.001$.

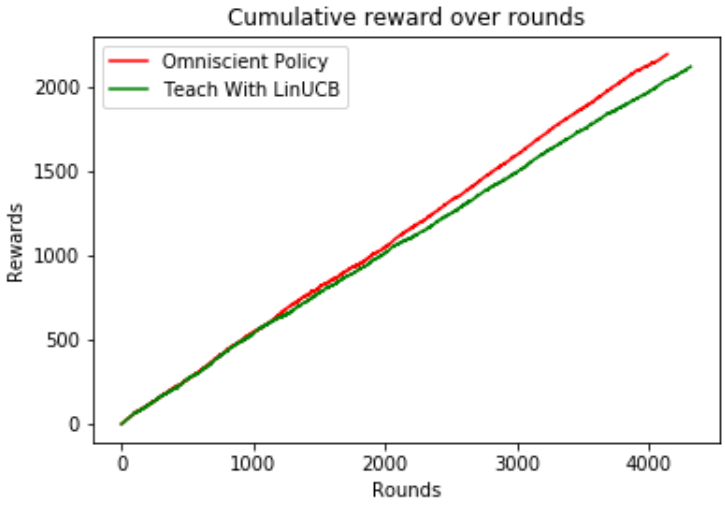


Figure 6.3: Cumulative Rewards With optimal hyper-parameters

The graph shows the performance of the learning algorithm is once again close to the omniscient policy.

Chapter 7

Conclusions

This project presents a student-centric approach to teaching. An approach, which could make classrooms more interactive by providing a personalized learning experience for students. We synthesized an unbiased dataset for our adaptive learning system, to represent heterogeneous student and content data to evaluate our learning algorithm. Since there were no benchmarks available, we created an omniscient policy which has optimal parameters pre-configured. We use these parameters to optimize the learning algorithm.

We then present a feature which would be useful when there are several different content items for a topic, to avoid students from getting frustrated with being stuck on a topic. This not only helps students but also helps teachers recognize topics students struggle with. We evaluated the learning algorithm to set a baseline for this new teaching methodology.

Our future work would involve creating an actual course that follows the teaching methods outlined in this project. This would give real student data, to evaluate the learning algorithms. We would also like to customize other algorithms to evaluate their performance against our baseline algorithm.

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