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Characterizing Academic Help-seeking Moods for Enrollment Performance of Institutional Online Student

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Abstract

Few could have anticipated the sudden and dramatic impact of COVID-19 on all aspects of life, including online academic help-seeking of institutional education. Academic help-seeking is a quite prevalent phenomenon that supports students to learn knowledge and improve academic performance. This study is aiming to understand learners and associate their performances via exploiting academic help-seeking moods with online learning of institutional education setting. Adopting the relevant theories, we propose a novel research model and identify three different online help-seeking moods, which are namely goal-directed seeker, exploratory seeker and avoidant seeker. Goal-directed seekers are described with preference for more challenging assignments and more posting on the platform discussion board frequently. Exploratory seekers hold the highest achievements during all help-seeking moods. Avoidant seekers are well-distinguished by holding the lowest frequency of posting among all moods and the most average time spent on the platform. Students have collective preferences for assignment submission in each help-seeking mood, and deviation from those preferences increases their probability of dropping academic grade significantly. To the best of our knowledge, this research is the first work that characterizes the help-seeking moods and associates moods with the enrollment performance for online education of institutional student.

Keywords: Help-seeker; Information Seeking; Online learning; Academic Resources; Education Informatization

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1. Introduction

The facilities including mobile devices, data storage and computing platform of modern information technology have greatly accelerated the integration of information technology and education practice, promoted the "Education Informatization 2.0" Plan, and provided a solid technical guarantee for the academic information-seeking [1]. As one of the most prominent features, online course or e-learning has been adopted widely by formal education institutes (e.g. schools, colleges, universities, etc.) and especially outbreaks due to COVID-19 pandemic. Consequently online courses accumulate a whole bunch of academic help-seeking data that provide practical and novel insight with the machine learning development. However, empirical statistics from online courses shows that information seeker and performances deviations are quite different from each other, such as 40%-80% of registered learners of societal education (the opposite of institutional education) tend to have low academic performance and have to give up before completing their second-month of membership [2,3].

Furthermore, the main streams to date in the related areas of education and information systems are only focused on societal online courses, such as Massive Open Online Courses (MOOCs) and Community Question Answering (CQA) websites [2, 4, 5]. Obviously, there is a research gap in the literature for studying academic help-seeking and enrollment performance in comparatively formal education institutes such as the setting context of school or college teaching platforms/course management information systems. Understanding the ways in which students behave while asking for information or help is fundamental in guiding the design of recommender systems and predicting their performances. Therefore, we focus on the study of characterizing academic help-seeking moods in the setting of university e-learning platform. Our research aims to inspect the academic help-seeking moods and enrollment performance of students in the context of the institutional education setting.

In this study, the main innovations and contributions to information systems and education management are described as follow by charactering online academic help-seeking moods. Firstly, what are online academic help-seeking moods? We investigate help-seeking moods of online students with the proposed model and identify the categories of help-seeking mood: goal-directed seeker, exploratory seeker, and avoidant seeker. Another one, how are academic help-seeking moods and enrollment performance correlated? The preliminary results show that help-seeking moods reflect online student cognitive and behavioral motivations, and lead to academic performance. Finally, according to prior study, the association between help-seeking moods and enrollment student performance can be investigated and applied to prediction.

This study is organized as follow. After the introduction, we present the theoretical concepts such as definitions of the theoretical terms and relevant research progress. In section 3, we focus on the model construction and deduction process for online help-seeking moods modeling. After that we illustrate the preliminary results by applying the proposed model to online learning platform of XXX University (XXXU). Then, by comparing with previous help-seeking research, the main contributions and implications of characterized online help-seeking for both academia and industry practice are discussed. Finally, the future research directions and improvements are drawn in the conclusion section.

2. Related Work

2.1. Help-seeking

As one kind of information seeking, academic help-seeking is an effective way for adaptive learning, which is regarded as a solution strategy for individuals to adjust their social environment to solve academic problems. Academic help-seeking is also different from other learning strategies, mainly reflected in the process involving engagement and social interaction [1, 6]. This diversity in computer-supported instruction has changed the nature of how learners interact with their helpers, and thus has also changed the nature of help seeking. According to previous literatures [7, 8], researchers usually divide academic help-seeking into three types based on motivation, which are Executive help-seeking, Instrumental/Adaptive help-seeking and Avoidant help-seeking. This study is inspired by the categories of asking for help that are introduced as follow.

When encountering academic problems in learning, the executive help-seekers directly use answers of certain questions or ask others to solve problem. It means they would like to choose dependence rather than independent
solving capability. Whereas, instrumental help-seekers tend to understand and master the process of solving problem instead of just getting the answers. Instrumental help-seeking not only helps learner solve problems, but also helps the seekers improve their learning ability. Researchers study individual differences in help-seeking behaviors as a way to understand avoidant help-seeking: why some learners do not ask for necessary help. Nevertheless, executive help-seeking and avoidant help-seeking are negative behavior patterns of help-seeking, which are not helpful to their performance. The progress of help-seeking category paves the main way and provides research direction for characterizing help-seeking with online learning setting.

2.2. Help-seeking Moods and Detection Techniques

Help-seeking mood is one kind of engagement moods with three most widely used conceptualizations including behavioral, emotional, and cognitive views [9]. In the context of help-seeking research, behavioral view refers to attention, participation, and effort a student puts in solving academic problem. The emotional view refers to students’ affective responses to problem solving activities and the individuals involved in those activities. The cognitive view is about how intrinsically invested and motivated students are in their help-seeking process. All the component views show features in practice for academic help-seeking which can be utilized according to different education settings.

Diversities of machine learning techniques for student moods are proposed broadly because of online data accumulation and complexity [3, 10, 11]. As one of the most popular of the clustering algorithm, K-means has been applied in extracting naturally occurring typology of students’ moods [12]. By comparison of similarities and dissimilarities between different features, researchers characterize 15 different clusters for learner moods. Another study investigates a combination of hierarchical and non-hierarchical clustering algorithms to identify the individual contributors’ profiles [13]. Researchers categorize contributors’ behavior into 10 types based on how much and how well individuals contribute to the platform over time. However, research evidences show that K-Means approach is helpful with the features condition of Euclidean distances properties.

Furthermore, Hidden Markov Models (HMMs) are latent variable models, which also attract much more attention due to powerful function. Semi-Markov Model is adopted for simulating and capturing student moods of MOOC [14]. This work provides a graphical representation of the dynamic transitions between different states, such as forum participation or video watching. Researchers propose to combine HMMs and Reinforcement Learning Model for characterizing users’ flow experience on an online judgement platform [5, 16]. Based on existing literatures, this paper is the first to use HMM to characterize academic help-seeking moods in course management information systems of Chinese university. Understanding online help-seeking moods can leverage institutes to manage teaching better and set more customized assignments for enrollment performance.

3. Research Model

3.1. Overview

In this study, an unsupervised HMM adopted is used for decoding online student help-seeking moods [3]. There are 2685 undergraduate courses records in the second semester of 2019-2020 XXXU (Fig. 1) range from March 1st to July 15th 2020. These course teachings are scheduled in classroom but actually online because of COVID-19 pandemic. The HMM components are trained with the student data features from the accumulated data. The HMM inputs are recognized as simple observable features that imply student achievements, challenge, endurance, and initiative states during the semester on platform. The HMM parameters adopted previous works by this paper can be estimated by iterations of Baum-Welch, a standard Expectation Maximization (EM) algorithm [3, 16]. There are three dominant help-seeking moods identified, which are (S1) goal-directed seeker, (S2) exploratory seeker, (S3) avoidant seeker. For the purpose of verification, a user study with 34 students of Business Analytics online course of XXXU is investigated to evaluate the help-seeker moods.

As powerful statistical tools, Hidden Markov Models are applied to make inferences about the latent/unobservable variables through analyzing the manifest/observable features [3, 17]. According to previous research on education information systems, HMMs are designed for the detecting various phenomenon such as
student social loafing, flow zone engagement, and academic pathway choices [5, 18, 19]. Those widespread literatures of HMMs and the HMMs capability of capturing complex data structures inspire this study to apply HMMs to distinguish between different student help-seeking moods in online institutes platforms with the module of Python.

After decoding the help-seeking moods with the HMM, we associate the platform assignments with the help-seeking moods that are more likely to submit solutions for those assignments. It’s obvious that online students have collective preferences in each help-seeking mood, and deviation from those preferences increases their probability of dropping academic grade significantly.

![Fig. 1. Undergraduate Courses of XXXU](image)

### 3.2. Inputs

The HMM based help-seeking mood model delineates the manifest features for student including achievements, challenge, endurance, and initiative (ACEI). These manifest ACEI features are proposed by performing an extensive thematic analysis which are listed as follows [11]. However, it’s emphasized that these features serve only as cues to infer learners’ cognitive (achievement and challenge) and behavioral (endurance and initiative) seeking moods for online students.

**Achievement:** The feedback of each assignment submission, such as the score, the result of academic grade, which is recorded on the platform.

**Challenge:** The pass rate of each assignment can resemble the degree-of-difficulty called challenge. It’s obvious that assignments are different with each other considering the challenge. The assignment is much more challenging with the lower pass rate.

**Endurance:** The time students spend on the platform to watch or download lectures, to post on discussion board, to take examination, to submit answers during a period of time in which the interval between two consecutive assignments is student endurance.

**Initiative:** The count of posting on the platform discussion board between two consecutive assignments is a learner’s initiative. This work measures the student interactive frequency during the interval of two consecutive assignments.
3.3. Parameters

A four-element vector \( O_t \) is utilized to refer to the corresponding student observations after each assignment submission to the platform in time \( t \). The observations \( O_t \) are generated by an underlying state space of hidden variables \( Z = \{ z_i \} \), where \( i \geq 1 \). A triplet \( \lambda_{\text{HMM}} = (A, B, \pi) \) is adopted to denote the HMM training for extraction of the student seeking moods. The transition matrix \( A \) means the probabilities of changing between different seeking moods over time. The emission matrix \( B \) shows the conditional probability for an observation \( O_t \) to be generated from a certain seeking mood \( z \). The vector \( \pi \) denotes the initial probabilities of being in each of the seeking mood \( z \). The initial probabilities are often assumed to be \( 1/|Z| \), and the \( |Z| \) means the cardinality of the hidden state space which is the number of seeking moods in this setting.

3.4. Model training

Following previous research this study optimizes \( \lambda_{\text{HMM}} \) parameters in the observation period with Baum-Welch a standard EM algorithm \([3, 16]\). The aiming role is to optimize the \( \lambda_{\text{HMM}} \) parameters such that \( \Pr (\lambda_{\text{HMM}}|O) \) is maximized with \( O = \{ O_t \} \). To avoid the local maximum problem when using the EM algorithm, the HMM is trained with ten random seeds until they converge at the global maximum.

The HMM representation of model is set up by choosing the best number of hidden states. Literally, this task appears to be simple conceptually. Practically, finding the appropriate number of hidden states in a meaningful way is quite a challenge. The main reason is that an HMM with a number of hidden states may not capture the underlying help-seeking motivations adequately, or an HMM with too many hidden states is difficult to interpret help-seeking phenomenon. Based on prior literatures, the conventional Akaike (AIC) and Bayes (BIC) measures are adopted in model training \([20, 21, 22]\). In this work, a HMM with \( |Z| = 3 \) hidden states is determined since the global values of AICs and BICs are the lowest measures.

4. Preliminary Result

4.1. Pattern Discovery

Data distributions within each hidden state can be applied to characterize and visualize the distinction between different help-seeking moods \([19]\). As above discussion, the features include the number of each grade, incorrect and accepted submissions, the average difficulty of assignments, the average time spent on the platform, and the frequency of interaction in initiative. These features are set to examine all students’ collective behaviors in a specific hidden state. The cumulative distribution functions of these features represent the comparison of patterns in different hidden states that are summarized as Table 1.

| Help-seeking Moods          | Achievement | Challenge | Endurance | Initiative |
|------------------------------|-------------|-----------|-----------|------------|
| Goal-directed seeker         | M           | H         | M         | H          |
| Exploratory seeker           | H           | M         | M         | M          |
| Avoidant seeker              | L           | L         | H         | L          |

Note: H=high, M=medium, L=low

(S1) Goal-directed seeker (Hidden State 1): The students in this mood are best described for their behavior performance of challenging assignments. They also attend the platform discussion board with the most times in comparison with the other help-seeking moods.

(S2) Exploratory seeker (Hidden State 2): The students in this mood do not prefer to specific-context assignments and regularly search for their information of interest. The students in this mood hold the highest achievements on the platform during all help-seeking moods.
(S3) Avoidant seeker (Hidden State 3): The students in this mood are well-distinguished by holding the lowest frequency of posting among all moods for attending the platform, which means that they seldom ask for help in the platform. Furthermore, the most average time spent on the platform is also another characteristic of this mood. Maybe, it means that with this mood students tend to review and find solution independently for assignments. However, the lowest achievements of assignments are the outcomes.

4.2. Evaluation

![Fig. 2 E-learning Platform of XXXU](image)

![Fig. 3 User Logs](image)
Avoidant seeker (Hidden State 3): The students in this mood are well-distinguished by holding the lowest frequency of posting among all moods for attending the platform, which means that they seldom ask for help in the platform. Furthermore, the most average time spent on the platform is also another characteristic of this mood. Maybe, it means that with this mood students tend to review and find solution independently for assignments. However, the lowest achievements of assignments are the outcomes.

4.2. Evaluation

Fig. 2 E-learning Platform of XXXU
Fig. 3 User Logs
Fig. 4 Assignment Grade

Table 2. Options of the help-seeking mood

| No. | Options                                                                 |
|-----|-------------------------------------------------------------------------|
| 1   | Help-seeking for submission of the assignment on time                   |
| 2   | Help-seeking for expanding knowledge and enriching yourself based on the assignment |
| 3   | Seldom asking for help                                                  |
| 4   | None of the above (details)                                             |

A preliminary evaluation with 34 students of Business Analytics Course at online platform of XXXU (Fig.2, 3, 4) to show the accuracy of the hidden states resolved. The participants are all undergraduate students including 13 females and 21 males in the age range from 19 to 23 (mean = 20.85, SD = 0.74). Participants are required to take part in this evaluation from their homes’ safety and comfort. The event-focused version of Experience Sampling Method (ESM) is adopted to collect the students’ help-seeking moods after each assignment submission to platform. These questions are to identify their moods through one of the options shown in Table 2. Parallel to each self-reported help-seeking mood, an HMM-based label is also generated through students’ observed data. It’s noticed that there is a consistence mostly with the help-seeking mood labels extracted from the HMM and ESM. Specifically,
none of the participants propose any moods other than the three help-seeking moods extracted. However, there would be more personalized and detailed help-seeking moods with an increased number of interviewees.

4.3. Help-seeking moods and grade point

In this subsection, the optimal $\lambda_{\text{max}}$ is used to identify the most probable help-seeking mood sequence $X_z = \{x \in Z\}$ for each online student considering their observed sequence $O$ in order to maximize the $Pr(X_z | O, \lambda_{\text{max}})$. We associate every assignment $q_j$ on the e-learning platform a distribution $Q_j$ based on the probabilities for receiving submissions when students are in different hidden states. Here, the index $j$ means the identity number of assignment on the platform. The average assignment mismatch is defined as the probability that a task does not match with the current help-seeking mood of a student. Obviously, the assignment mismatch is the complement of the task’s associativity measure.

Furthermore, the null hypothesis is proposed that the average assignment mismatch has no correlation with the online student academic grade so as to understand help-seeker. The preliminary regression analysis reveals the positive coefficient factor significantly between the average assignment mismatch and the student academic grade. Theoretically, the null hypothesis is rejected that means with the average assignment mismatch increases, the percentage of online students low grade increases. Additionally, it can be inferred that the students in each help-seeking mood have a collective preference for assignments if from which they deviate, the risk of dropping grade also increases.

5. Discussion

Seeking academic help when needed is an important adaptive self-regulated learning strategy that supports students to learn knowledge and improve academic performance. Our study is aiming to understand help-seeker and associate their performances via exploiting online academic help-seeking moods under the institutional education setting. Based on the relevant theories and techniques, we propose a novel approach and identify three different help-seeking moods, which are namely goal-directed seeker, exploratory seeker and avoidant seeker. Online students have collective preferences for assignment submission in each help-seeking mood, and deviation from those preferences increases their probability of dropping academic grade significantly.

The online help-seeking mood research and implications can provide insights relevant to both academia and practice. In academia, help-seeker mood model with proper category is the beginning model of help-seeking process that is neglected by most literatures [6]. This study fills this gap by extending HMMs to help-seeking moods area and investigating collective preferences of help-seeker. Practically, rendering and exposing help-seeking moods can provide insights for online learning professionals of formal education institutes to manage students’ behaviors better and tailor their services accordingly. Another implication is emphasized that people change their behaviors dynamically over time. Therefore, studying the dynamics between help-seeking moods is an essential part of understanding students’ behavior. Based on the observations from help-seeking mood changes, the transition probabilities between different help-seeking moods can be calculated and utilized to guide assignment arrangement and curricula.

6. Conclusion

Academic help-seeking is an important adaptive self-regulated learning strategy. Various models of the help-seeking process include some combination of seven steps [6] that neglect the first and most important question: what are academic help-seeking moods? This research investigates online help-seeking moods with the powerful tool HMM to expose underlying the categories of help-seeking mood: goal-directed seeker, exploratory seeker, and avoidant seeker. Goal-directed seekers are described with preference for more challenging assignments and more posting on the platform discussion board frequently. Exploratory seekers hold the highest achievements during all help-seeking moods. Avoidant seekers are well-distinguished by holding the lowest frequency of posting among all moods and the most average time spent on the platform. To the best of our knowledge, this research is the first work that characterizes the help-seeking moods and associates moods with the enrollment performance for online
platforms of institutional education.

Our future work includes developing a useful prediction approach for enrollment student academic grade and enriching the explanations to performance prediction. Based on this study, sources of academic help is another key theme of help-seeking and are on our research agenda. Returning to the context of the higher education setting, we recommend that institutes of higher education a) specifically consider how educational technology has changed the nature of help seeking, b) assess from whom, what, or where each kind of help-seekers want to and are actually seeking academic help, and c) make necessary adjustments to encourage students to seek help from the sources that will be most effective according to their temporary help-seeking moods.

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