Evaluation of student perceptions and interests using Spoken Tutorials in online courses.

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***Abstract*— We evaluate the perceptions and the intensity of students who study online courses using video tutorials. Using the data of the past viewers, and the concept of similarity of interest, we recommend videos for further learning. As the total number of videos in the repertoire is large, this helps reduce the information overload. Although spoken tutorials are used for this study, the results are generic. This work is based on an empirical model obtained through a data mining approach.**

***Index Terms*— Spoken-tutorial, e-learning, clustering, student interests, student perceptions**

I. Introduction

Spoken tutorial [1],[2] is a screencast of an expert demonstrating a computer based activity, created for self learning. Spoken tutorials are typically of 10 to 15 minute duration, containing about one hundred screen transitions. The spoken part of the video is dubbed into all Indian languages. A two hour workshop followed by self study and an online test helps complete 10 to 12 tutorials, forming a course. The test has 30 questions on various aspects of the content matter. The students also rate the videos. This effort is supported by an online portal, designed with student feedback [3]. Suitability for self study and the online portal have made this effort extremely popular, resulting in 200 to 300 workshops every month, training about 30 students in each workshop. The data collected in these workshops form the basis of the current work. With the growing demands of online courses, students are exposed to several forms of audio-video content to enhance their knowledge through virtual classroom environments. They also spend a lot of time to search for the content they need. Collaborative views and recommendations [4] of the past students have been used to reduce the time involved in search and retrieval of content. In recent years, recommender systems have emerged as one such tool that can help people overcome the problem of information overload and quickly locate the content of their choice. But these approaches have the following drawbacks.

Although there exists a lot of literature to predict the student interests and preferences based on heuristic data, there is not much work to study the number of times an article is viewed, article type, language of the content viewed and the prior experience of the student. These factors could influence the interest of the students.

The student interest towards a particular video content depends upon the duration of exposure and intensity of interest aroused. These interests can be of short-term or long-term. The students who watch videos for a shorter duration do not rely on the recommendations and views of the past students. They mainly use the ratings of the videos. On the other hand, the students with long term interest do just the opposite: they give more weightage to recommendations and views of the past students, as opposed to simple rankings. Of course, they also rely on their prior experiences and a knowledge of the topic matter [5]. The current approaches fail to estimate these factors. It has been argued that the following factors can influence the student's perceptions and interests [6]: duration of interest, magnitude of interest - long-term or short-term depending on the duration of exposure, language, cognitive style, gender and past experiences, with the last three being more important than the rest. In the current work we propose a framework to automate the identification of student perceptions and interests using spoken tutorial based instructions. We examine whether the findings of [4], [5], [6] are valid in the Indian context. Although this exercise has been conducted using spoken tutorials, we would like to explore whether the findings can be generalized.

II. Research Methodology

1) Research Questions: Spoken tutorials have been chosen as the candidate to understand the behavioral interventions of the learner. The idea is to automatically predict the interests and perceptions of the learner while watching these videos. The research questions examined in this study are:

- Do behavior interventions help in understanding the student interests and perceptions while using spoken tutorials in online courses?
- What is the role of learner preferences in online courses conducted using spoken tutorials?

Thus, behavioral interventions and impact of spoken tutorials in online courses are studied in this work.

2) Measurements and Method: The research sample for the study is a set of 2,000 feedback obtained from 500 students. These are given after having undergone workshops and a post test on the following four subjects: Linux, LaTeX, Python and Scilab. Some measurements are already available at the beginning of this work. These are: (1) Statistics of previous views of a tutorial (2) Ratings of tutorials on a five point scale by the previous viewers

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(3) Suggestions given by the past viewers. In the current work, the following additional measurements are made: (1) Questionnaire: Demographic details and the video watching preferences of students. (2) Video watch time: for how long a student watches a particular video. The time spent by a student A in watching a tutorial i in a given session is denoted by t_{Ai}. (3) Intensity: frequency of watching a tutorial in a given session by a student. The number of times a student B watches a tutorial j in a session is denoted by N_{Bj}. They are given *video suggestions*: they are told what other videos are watched by those with similar interest, who had viewed the current tutorial. The procedure to predict the similarity of interest is explained subsequently.

3) Implementation Framework: Student interests aand perception model comprises an online web based interface with access to various FOSS course video tutorials. The implementation framework of the interface comprises of a student interest modeler with cluster and perception analyzer, video module, and assessment tool. Student module captures the details of students, profiles, visits. While video module provides videos based on language, name of tutorial and interest ratings given[7]. Student interest modeler predicts the student interests[8]. And clusters the students into interest groups using cluster analyzer. Student repository is integrated with all the modules to recommend videos based on student interests and perceptions computed by this framework.

III. Mining Model of Student Interests and Perceptions.

A. Prediction of who watches spoken tutorials

Students past experience and learning preferences also influence the interests and perceptions towards a video tutorial. Students who usually play several hours of video-games, surfing and watching movies seem to possess more interest in video courses. The converse also is true: those who did not enjoy video-games, etc. did not like video courses [9]. In our study, 62% of the people belong to the first category and they showed a lot of interest in the spoken tutorials. The remaining 38% of the students did not play video games, and they also did not show as much interest in the spoken tutorials. It is likely that this group includes the students who eventually failed in the test conducted post workshop, which is of the order of about 15%.

1) Similarity of Interest: In this section, we explain how we have estimated the similarity of interest of student A with student B on a particular interest point in the interest set. The interest point in our case is a spoken tutorial, for instance, the tutorial on *synaptic package manager*, while the interest set is the entire set of tutorials on Linux.

Recall from Sec. II-.2 that N_{Ai} denotes the number of views of tutorial i by A. Let the similarity of interest between two students A and B for a particular tutorial j in a family of V number of tutorials be denoted by $I(A, B, j)$. Then we have

$$I(A, B, j) = \frac{\sum_{i=1}^{V}(N_{Bi} - N_{Bj})(N_{Ci} - N_{Cj})}{\sum_{i=1}^{V} N_{Bi} \sum_{i=1}^{V} N_{Ci}} \quad (1)$$

In other words, it is the product of visits to all *other* tutorials in that course, scaled by the total number of visits. If the number $I(A, B, k)$ is large, we say that the interests of students A and B in watching the tutorial k is similar. If on the other hand it is small, the interests are dissimilar.

Semantic categorization of tags and keywords based on the past learners' preference helped summarize the videos. The videos were displayed according to this categorization. Longer the duration spent in watching a video, more curious and stronger are the interests of the student. We can identify the interest developed towards a particular video by clustering the students into interest groups of similar and dissimilar interests [10].

2) Long-term and Short-term classification: We next classify the students with *similar interest* into two groups: long-term and short-term. Recall the definition of symbols t_{Ai} and N_{Ai} from Sec. II-.2. Let $\bar{t}_i$ denote the *average* time spent by *all previous viewers* on tutorial i. Similarly, let $\overline{N}_j$ denote the average *number* of visits by all previous viewers to tutorial j. If the duration and the number of visit are greater than the corresponding averages, we say that this is an evidence of long term interest, i.e., $t_{Ai} > \bar{t}_i$ and $N_{Ai} > \overline{N}_i$ indicates that the student A has a long term interest in the tutorial i. Both being less indicates short term interest. That is, $t_{Bj} < \bar{t}_j$ and $N_{Bj} < \overline{N}_j$ indicates that the student B has only a short term interest in the tutorial j. If on the other hand, any *one* of them is less and the other greater than the corresponding average, we conclude that the student possibly liked this video in the past, but not now. Comparing the rating given by a student on a five point scale with the average rating of the previous viewers with long-term interest, is another way to classify the duration of interest. If the rating given by the student is higher than the average, they are said to have long-term interest in that tutorial. A student who satisfies any of the above discussed two conditions is said to have long-term interest.

The student interest is also predicted based on the ratings given for each and every video watched during the workshop [11]. For every spoken tutorial, the students can be grouped into those having long term, short term and neutral interest. By assigning weights for the different types of interests, one can assess the efficacy and the usefulness of a given tutorial. This will be an experimentally determined rating factor of the tutorial. This could be useful to the content creators and learners.

B. Recommending spoken tutorials

The students may not be aware of the courses that suit their interests, especially if a lot of content is available [5]. The video suggestion helps address this issue. This is perhaps the most useful outcome of this work from the student's point of view: to get a recommendation on

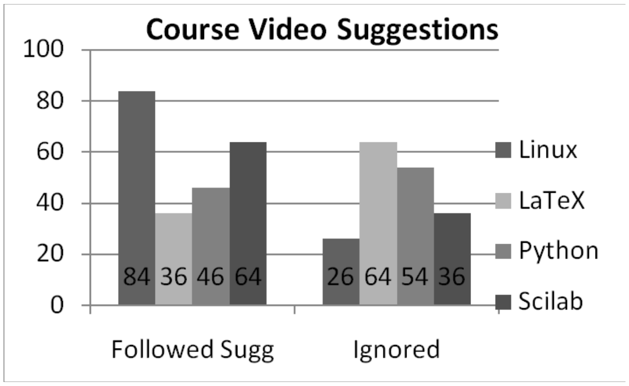

Fig. 1. Spoken-Tutorial Video suggestions

tutorials to watch. We find the students with a similar interest and make a recommendation based on whether they fall in the long-term interest group or not. We now give the algorithm for an arbitrary student with a long-term interest, L, who watches a spoken tutorial, i.

1) Using the procedure given in Sec. III-A.2, all students who have a *long-term* interest in a video i are grouped. Call this set of students as Φ_{Li}. Note that these students have an interest similar to L, as the classification into long-term and short-term is done on similar interest groups only.
2) For every student $A \in \Phi_{Li}$, group the videos they liked into a set Ψ_A. Any video seen for longer than the average time spent on all the videos by the student A is said to be *liked* by A.
3) Any video that has a larger than the average frequency in $\Phi_{Li} \times \Psi_A$ is said to be strongly correlated with the video i.
4) The videos with high correlation are recommended to a student L who watches the video i.

The recommendation for students with short-term interest is based on a procedure identical to the one above, but for a change in Step 3. For students with a short-term interest, the recommendation is based on ratings on the five point scale, rather than the time spent. A breakup of the students who have followed and ignored the video suggestions is shown in Fig. 1. The students may ignore the video suggestions for the following reasons: (a) perhaps they are casual visitors (b) they watched the tutorial mainly to pass some test, but not genuinely interested in the subject matter (c) they did not have sufficient time to watch other videos. One can see that more number of people ignored the suggestions on $\LaTeX$ and Python, compared to those who followed. This suggests that these two FOSS systems are possibly not popular or not required in their curriculum. Linux and Scilab seem to be more popular or at least useful.

IV. Conclusions

Student interests and perceptions are predicted based on questionnaire, video ratings, duration of videos watched and past students ratings and suggestions. Using these and the frequency of viewing tutorials, an automatic recommendation system has been developed. Although we have not reported, the language used along with the English screencast also has an influence in improving the interest level in watching video tutorials. Our findings are similar to what has been observed by [5] and [6]. The video recommendation feature has several benefits. First of all, it reduces the information overload: the student does not have to wade through all the videos to decide what all they would like to watch. It has the potential to convert short term interest students into a long term interest by a suitable sequencing of tutorials.Through the recommendation system, we can also hope to improve the learning habits of students. we believe that these findings can be applied to any other well designed self learning system also. The reason is that there is nothing special about a spoken tutorial, except that it is created for self learning so that even a child from remote locations can understand it without assistance from an expert [2].

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