Reviews Evaluation for Online Courses: A Deep Learning Technique / Approach.

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Abstract

The amount of information available online is become harder to keep up with, which has increased information overload. Recommender systems have been developed to address this problem and can offer users learning resources depending on their interests. Students from MOOCs frequently discuss their educational experiences and other course-related topics in the discussion section. These comments can be an indication of how students feel about taking online classes. However, the semantic information tucked away in these comments might assist teachers in improving the appeal of their courses and assist other students in choosing better courses. There hasn't been much research done lately on using review mining to evaluate courses. An assessment method is developed using MOOC reviews for curriculum from diverse disciplines. A topic-word distribution matrix and a comment-topic distribution matrix are produced using the Latent Dirichlet Allocation (LDA) technique. A LSTM classification model and an auto-encoder are used to determine each subject's emotional value. We develop a comprehensive technique for assessing courses on a range of topics by combining subjective and objective evaluations.

Keywords— Curriculum evaluation, review mining, text classification, emotion analysis.

I. Introduction

Online implementations in Education sector is widely popular during this decade due to Covid-19. This scenario enforces various recommendation methodologies to evaluate the performance of such online courses on the basis of reviews mainly based on preferences and expertise, as well as data from other learners (reviews) with similar interests.

Large repository of data is being created due to the increase in both instrumental online educational system and collection of tremendous data (users' information and tutor's information along with study material) leads to new concept called as e-learning or web-based learning. [1].

Learning modes are mainly classified in three categories:

1. Way of transmitting the knowledge and skills based on eye-to-eye contact and also observing and learning human being learning process by psychologically is mainly termed as Offline mode. For analysis purpose, Psychometrics and statistical techniques have been applied to data like student behavior/performance, curriculum, etc. which is collected in classroom environments.
2. Way of transmitting the knowledge and hence instruction through online is termed as Online mode. Various software applications in this mode provides communication, collaboration, administration and reporting tools. For analysis purpose, Web Mining (WM) techniques have been applied to student data

stored by these systems in log files and databases.

3. An alternative mode is "just-put-it-on-the-web" approach is by trying to adapt teaching to the needs of each particular student as per his/her convenient time is termed as Intelligent Tutoring (ITS). For analysis purpose, Data Mining has been applied to data picked up by these systems, such as log files, user models, etc.

Chapter 2. Related Work

Modern educational systems use a range of recommendation techniques to give online learning activities based on student choices, subject matter expertise, and data from other students with similar interests. These study subjects are growing (Romero and Ventura, 2010). The author uses the user logs and content of the e-learning system to suggest materials to students.

A MOOC assessment system by Drake et al. [2] incorporates quantitative, qualitative, and curriculum-focused evaluations. And it outlined with the five guidelines for MOOC teacher to follow creating and overseeing large classrooms. These five principles—meaningful, engaging, quantifiable, accessible, and scalable—were combined with information systems theory and conceptual development.

Five first-level indicators—course content, instructional design, interface design, media technology, and curriculum administration—should be incorporated into an evaluation framework based on data mining and ambiguous set methodologies, according to Miranda et al. [3].

Nie and co. [4] Propose a diagnostic method to MOOC assessment that incorporates expert views, standardised rubrics, and student input into the evaluation process using the analytic hierarchy process algorithm.

To predict MOOC learner happiness, Hew et al. [5] employ gradient boosting trees and a sentiment analysis strategy. This study extended the theoretical framework by using student satisfaction as a metric of MOOC success. knowledge of the elements that can influence MOOC learner satisfaction. It provides three contributions to the field: (a) It quantitatively examined information pertaining to randomly chosen MOOCs; (b) It offers a novel methodology (supervised machine learning and using sentiment analysis, we evaluate a sizable dataset of user-generated reviews from users; (c) It details the particular learner-level and course-level variables that can affect MOOC learner satisfaction is predicted, and their proportional effects are estimated.

Zhao el al. [6] Three types of learning quality evaluation are the emphasis of the technique for assessing learning quality that is suggested.

Liu and co. [7] Designed a framework based on emotion recognition and topic mining in anticipation of MOOCs becoming more and more popular, to help teachers and administrators enhance their instructional strategies and enhance platform user experience. Online education will inevitably move from a screening phase to an accumulation phase as the scope of available resources grows. The findings demonstrate that words that reflect each topic have a higher degree of polymerization. The model is also used to mine emotion-topics from course units; important emotion-topic details for each course unit may be inferred from the probability distribution of emotion-topic words

Using Weng et al. [8] Professors may benefit from using MOOC evaluations to better understand the causes of their students' emotional swings so they can adjust or customise their instruction accordingly. to fully understand the role that feelings play in the learning experiences that MOOC participants have.

Machine learning approach developed by Xing et al. [9] to automatically identify feelings of achievement in forum postings.

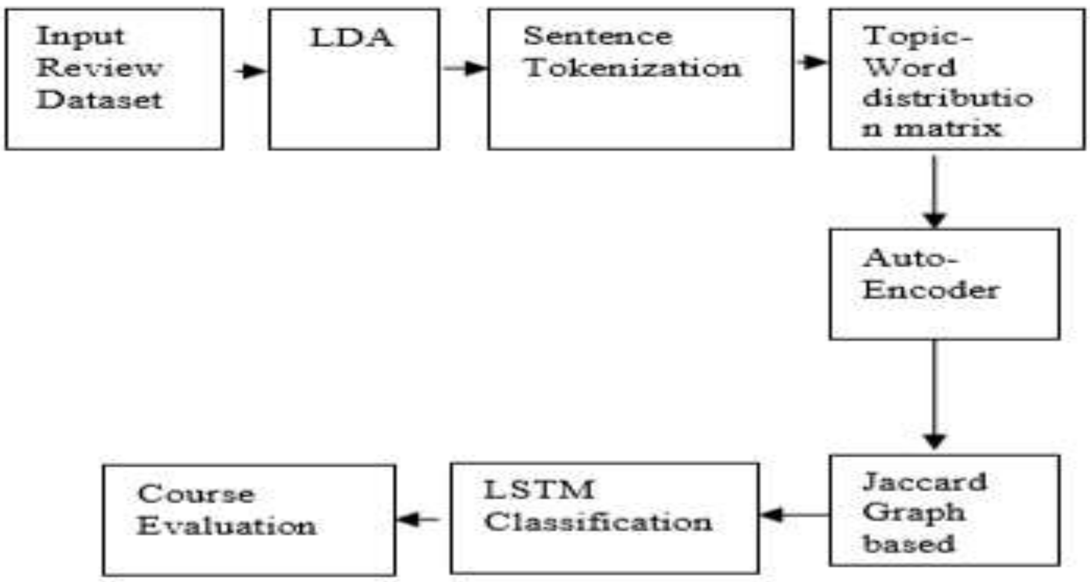
The behavior-emotion topic model put forward by Peng et al. [10] can be used to identify the review's semantic content, analyse notable variations in discourse behaviours, and concentrate on topics that differ between completers and non-completers. The emotive analysis of MOOC reviews has also advanced significantly, thanks to several academics.

According to Onan et al. [11], an effective framework for sentiment classification of MOOC evaluations is proposed. It is based on deep learning, ensemble learning, and traditional supervised learning techniques.

Chapter 3 . Methodology

- Dataset Input.
- Sentence Tokenization
- Topic Word Distribution Matrix
- Auto-Encoder
- Jaccard Graph-based Similarity
- Course Evaluation

Chapter 4 PROPOSED Method



- LDA

A short LDA topic as an alternative to the lengthy LDA subjects. The LDA topic model, which now incorporates sentence-level information, may now be used to account for text qualities that characterized comment messages, such as their short text length, sparse content, and lack of word co-occurrence information. The unique subject of the connected phrase should be extracted after the comment texts have been broken down into sentences in order to more precisely classify themes.

- Sentence Tokenization

Adding a new layer between the text and subject layers resulted in a "short comment sentence-subject-word model" has been developed.

There is a short text in each comment:

In order to construct the unique subject for this short phrase, In order to choose terms from the topic-word matrix φ, we employed the review-topic matrix.

- Topic-Word distribution matrix

For each of the z topics, the subject-word distribution matrix φ z is shown. Dirichlet distribution of parameter β is the polynomial distribution, which may be expressed as:

$\varphi z \sim Dirichlet(\beta)$

For each of the following remarks: The Dirichlet distribution of parameter α describes the topic distribution matrix θd, which may be expressed as follows:

$\theta d \sim Dirichlet(\alpha)$

- Auto Encoder

Unlabeled data may be encoded more efficiently using an autoencoder, a sort of artificial neural network (unsupervised learning). An effort is made to recreate the input from the encoding in order to verify and enhance it. In order to reduce the dimensionality of a dataset, the autoencoder trains a neural network to disregard data that isn't important to the dataset's representation (encoding).

- Jaccard Graph-based Similarity

Distance in Jaccard's terms. The proportion of intersection and union of words is used to compute the Jaccard distance, which measures the degree of similarity between sentences.

The equation below is used to compute the Jaccard distance in this study.

$$J_{a,b} = |word_a \cap word_b| / |word_a \cup word_b|$$

- LSTM Classification

LSTM Classification: Since it cannot store back-to-front information, LSTM, a deep neural network classifier, requires development for MOOC review texts.

It is fairly uncommon to hear students complain that their teacher's accent makes it difficult to understand what they are saying.

Which is dreadful" is used to modify the word "accent" in this statement. However, a one-way LSTM is unable to gather this information. A Bi-LSTM is used in this article to completely comprehend the semantics of the current words by capturing all relevant background information.

Chapter 5 Expected Result

The proposed Module is used in the education field, the one can search the Online courses according to their needs and specification. Without loss of time it will recommend the online Courses from the online platform.

Fig . 1 File path for the Recommendation of online courses.

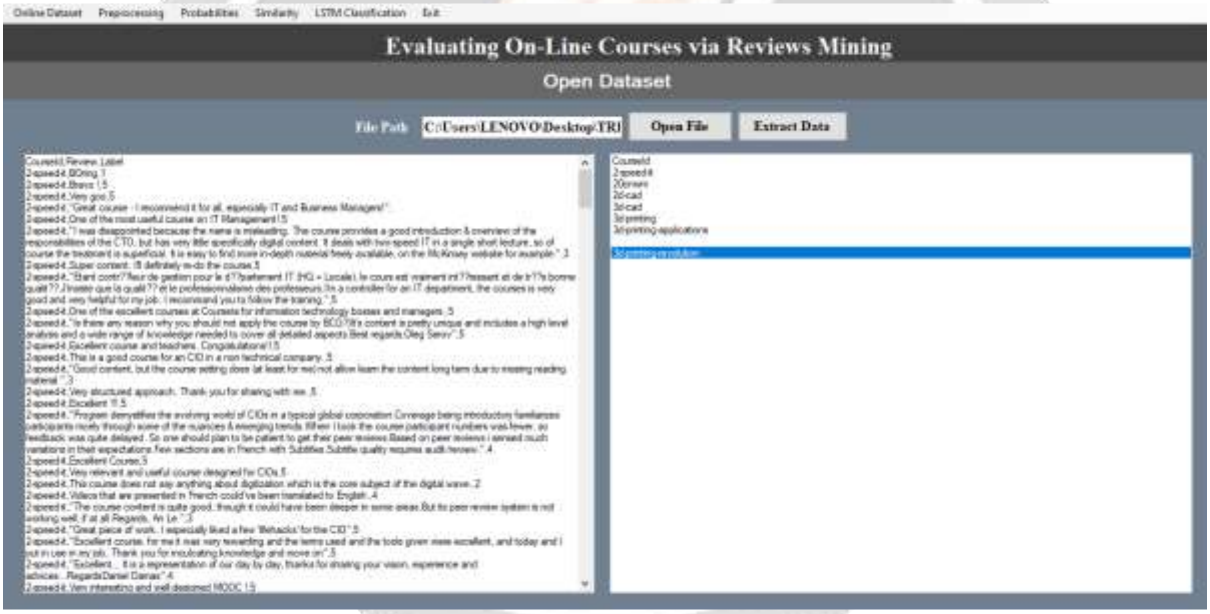


Fig 2 Recommendation of the online Courses.

CONCLUSION

As a result, we conclude that MOOC managers and institutions will be better equipped to improve the platform infrastructure and student service experiences in MOOCs. In the Fast and Developing Technology the focus for the MOOC (Massive Open Online Courses) is increasing.

Even while we've been focusing on MOOCs as a source of recommended material, this strategy might very well be used elsewhere. In fact, feature topic extraction may be used to include more domains.

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