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Recommendation System Based on Video Processing in an E-Learning Platform

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Abstract: With online learning technology fatly growing, especially with the Covid-19 pandemic, learning resources are produced in massive amounts, with high heterogeneity, and in numerous media formats. The key issue for today's learners is how to access the required learning resource based on their preferences and skills? Learning videos have become the central role in e-learning of higher education institutions. As a learning content, videos prove it is an important and necessary content delivery tool in all online platforms such as online, flipped, and blended classes. Hence, indicating suitable videos in seminal years possibly will help to do research in a better way. In this article, we present a recommender system that will suggest and guide learners in choosing appropriate learning videos per their requirements. Our system is based on collective intelligence. Indeed, we analyze the comments of Internet users on the videos to extract their opinions and then compare them with the evaluations to obtain a better recommendation.

Keywords: recommender system, e-learning, learning video.

电子学习平台中基于视频处理的推荐系统

摘要：随着在线学习技术的迅猛发展，尤其是在Covid-19大流行的情况下，学习资源被大量生产，具有高度的异质性，并且具有多种媒体格式。当今学习者的关键问题是如何根据自己的喜好和技能访问所需的学习资源？学习视频已成为高等教育机构电子学习的核心角色。视频作为一种学习内容，证明了它是在线、翻转、混课等所有在线平台中重要且必要的内容交付工具。因此，在开创性的年份指出合适的视频可能有助于以更好的方式进行研究。在本文中，我们提出了一个推荐系统，该系统将建议和指导学习者根据他们的要求选择合适的学习视频。我们的系统基于集体智慧。事实上，我们分析互联网用户对视频的评论以提取他们的意见，然后将其与评价进行比较以获得更好的推荐。

关键词：推荐系统，电子学习，学习视频。

1. Introduction

During the COVID-19 pandemic, the delivery of e-learning resources over the internet increased greatly as the need to access these resources remotely became more urgent. At the same time, the use of online resources provided educational institutions with an opportunity to try a new learning style and explore its advantages [1]. The greatest benefit of delivering learning materials over the internet was that there were no restrictions on the time and place of the delivery; in addition, students accessing the material received the same content no matter how many were in the course. Despite these benefits, educators have found that this learning alternative did not improve the learning process; therefore, a new flexible delivery paradigm may not be the main target, but there is an urgent need to enhance the learning process [2].

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Video content is one of the most important forms of online learning because it can simulate in-person lectures. Many online platforms offer various courses using video formats, including Coursera, edX, Udacity, iversity, FutureLearn, and Khan Academy [3].

The e-learning environment employs a recommender system to suggest suitable items (learning materials) to relevant users. There are many examples of real-world recommendation systems; the most famous of them is Amazon, which provides book and movie recommendations from Netflix [4]. As noted, web-based learning has grown rapidly, which has led to increased challenges in producing recommender systems for learning resources; consequently, this has become a highly popular research topic [5].

An e-learning recommender system provides learners with learning resource recommendations based on their preferences. Many online learning platforms offer recommendation agents to guide learners, but the assistance provided is very limited [6]. Learners need more expectation of knowledge agents to access reasonable learning resources [7].

As stated above, video lectures are the most significant format captured in classrooms because they provide a large amount of educational content. The format is easy for students to access because it involves motion, the adaption of time and space, and a safe environment, making the video lecture superior to textual and graphic media [8]. Videos also offer the ability to control the presentation (i.e., replaying, viewing, pausing), which helps learners review the video lecture as needed, unlike traditional in-person lectures. Many universities and websites host corresponding video lectures; examples of these online platforms include Coursera (https://www.coursera.org/) and Khan Academy (https://www.khanacademy.org/). Universities such as Stanford and MIT produce their own resources for distance learning. In addition, a wide variety of video lectures are uploaded daily to video sharing sites, such as VideoLectures.net (http://videolectures.net/) and YouTube (https://www.youtube.com/). In the last two years (since the beginning of the COVID-19 pandemic), the consumption of video lectures has increased rapidly, as many institutions have uploaded their video content, giving viewers free access on demand. E-learning videos represent a substantial portion of this viewing consumption because of the increase in requests for multimedia content related to online learning [9].

Along with the increased consumption of online videos, a new problem has emerged: information overload. This has made it necessary to provide learners with an automatic video recommendation system to provide a list of relevant videos that match their needs. Hence, many researchers and commercial institutions have dedicated their efforts to producing video recommender systems. YouTube, Yahoo! Video, and Bing Videos are commercial sites that use the deferent information format to build their recommender systems, which often depend on videos' textual data and the profiles of registered users. In general, good video recommender systems should be built based on an analysis of users' interests by observing the history of use or user profiles [10].

2. State of the Art

In this section, we present state-of-the-art work on the e-learning video recommendation approach, focusing on work that relates specifically to the problem. Therefore, we will discuss recommender systems built on user reviews and comments, the topic model, and the latent factor model (LFM).

2.1. Problem Statement

Usually, most recommender systems and search engines use explicit data about queried items, such as the video title, tagged keywords, or both. This data is often not enough to access suitable videos based on learner requirements. To access appropriate videos, we need more information about the video content, such as academic and student levels, to avoid examining a huge list of recommended videos.

Most learning video recommendation systems suffer from the inability to pinpoint appropriate e-learning videos, which leads to the teacher's failure to find appropriate materials. A better solution is to use a content-based filtering approach because it makes video suggestions based on the context and suitability of the learners.

2.1.1. Description of the Problem

Historical rating of learning videos helps learners make the right decision about which video will be suitable for them. Data may not be available, and it may not be clear because it usually takes the form of a number between 1 and 5 stars. This number represents the degree to which the learner liked the video without any additional information or details about the video content or the reason for the rating.

As a result, we acquired additional review data about the learning videos. These user reviews of learning videos will improve recommendation techniques more than using rating data, especially in the e-learning domain. By focusing on descriptions of the content specialization of videos, the video recommendation system can be more helpful to educators. For example, the review should include the following:

1. Brief description of the content;
2. Comprehension level of the learner;
3. Academic level of presentation.

2.1.2. Suggested Problem Solution

As stated earlier, we intend to use student review data on learning videos in our proposed methodology.

First, we will extract information from reviews, considering student preferences and learning resource features, such as the video subject/topic and learner suitability. This additional information will give learners more flexibility in selecting the right video for e-learning programs; it will also increase the accuracy of recommender systems. In this paper, we present a methodology for recommended video e-learning based on user historical reviews, rating data, and the content of video learning. The proposed technique can be implicated to support the learner with the necessary information to help him/her choose the appropriate learning video. Using a content-based filtering approach in an E-learning recommender system provides wide knowledge about learning content. It will be valuable for making the recommender system more personalized and improving its accuracy.

2.2. Related Work

Recently, in the E-learning field, the huge number of information released an overload problem. Hence as a common-sense solution, an effective recommendation system became an urgent need. The recommender systems are classified in [11] and [12] based on the techniques used to build them: stander collaborative filtering, content-based, hybrid technique, knowledge-based, utility-based, and demographic-based recommenders. Another researchers introduce modern approaches such as context-aware-based [13], trust-aware-based [14], fuzzy-based [15], social network-based [16], ontology-based [17], and group-based [18] techniques. [19] proposed e-learning recommender system using CF and APA techniques. That approach makes the learning method more personalized by providing the most suitable learning resources to the user. The researchers, in their methodology, defined a score function for learning resource scorning and used APA to gain an implicit rating to enhance prediction accuracy. CF was used to select the appropriate resource from learning object repertories based on the score function. [20] introduce a MOOC-based OER recommender system (MORS) that can be plugged into an online learning environment (OLE) to deliver suggestions of open educational resources to the user according to their profiles. They used metadata to access the course profile and determine the recommendation process. The proposed approach was implemented in a Massive Open Online Courses (MOOC) platform, Open edX, and can be used for any other online learning environment. The application presented in [21] exploited users' essay writing to get their knowledge and produce a digital library of resource recommendations by automated assessments and predicted their preferences through essay writing. The presented application was considered within the Customized Learning Service for Concept Knowledge (CLICK) environment, and the lessons learned were reviewed. [22] proposed a hybrid filtering technique to suggest a suitable learning object to users who have different preferences. They used text analysis to order the learning object based on topics and grouped users based on the similarity of their learning preferences by tracing and recording learners' behaviors. Hence, they constricted two level user profiles according to group preferences and text analysis. Then, learning objects are suggested to the learners based on their profiles through collaborative and content-based filtering.

A smart learning technique based on recommendations was proposed in [23], whose approach aimed to recommend suitable Arabic documents in smart campuses. The model was introduced as a decision support tool for mobile learning to provide personalized items to users who change over time, taking into account their contextual information and level of satisfaction and enhancing the quality of learning and the idea of collaboration in a smart learning platform. Xu and Zhou in [24] used deep learning models to get features from learning courses to build a course recommender system. In these models, they used many types of information from learning courses, such as comments, audio, and titles, to produce appropriate course recommendations in an e-learning environment. Furthermore, they used real-world data sets and considered implicit and explicit information to calculate users' interests. They perform an AUC score of 79.03%, as their result shows.

3. Proposed Approach

3.1. Methodology

In this part, we will describe our proposed recommender system to meet students' needs for learning videos on the E-learning platform. Our approach is a combination of a content-based (CB) recommendation system and a convolutional neural network (CNN) (Fig. 1-3), which runs in three levels:

Level 1 described CNN input as a language model of existing learning video resources. The output is the latent factor model (LFM) of students' historical data, normalized by the L1-norm. We use the students' comments and reviews on learning videos as training data for LFM. This kind of information could be explicit in the form of free writing text by learners or implicit, acquired from learners' behaviors. We exploited machine learning (ML) tools to convert source learning video to text without any information loss to use acquisition text as input data for the language model. This level is preprocessing for preparing input/output data to train the CNN model.

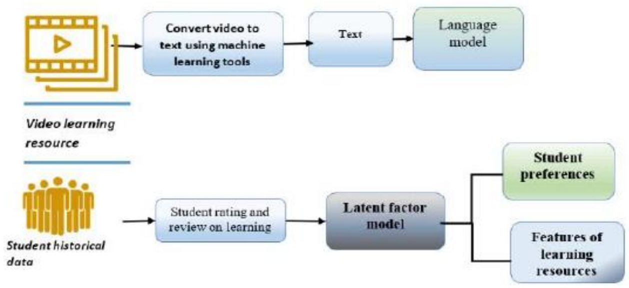

Fig. 1 Level 1 of the proposed technique

Level 2: We will train all CNN parameters by input and output.

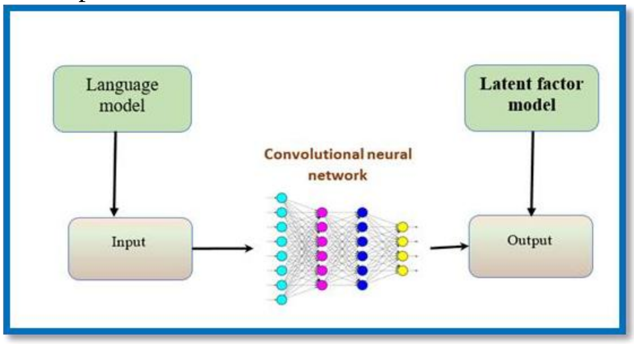

Fig. 2 Level 2 of the proposed technique (training level)

Level 3: Handling a new learning video resource recommendation process.

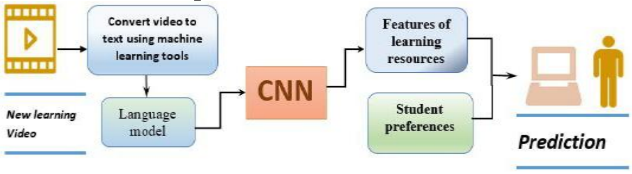

Fig. 3 Level 3 (recommendation level)

This framework consists of two processes: training represented in Levels 1 and 2 and recommendation represented in Level 3, which include input source learning video after passing converting operation to obtain textual information, which is brief text representing the content of input learning video. The textual information is inputted to CNN to extract the source input learning video features. Then we will combine these features with students' preferences to analyze the process of learning resource review to make the right prediction. This recommendation framework can predict if students would like to watch the desired learning video or not.

3.2. Proposed Approach

This section clarifies how we build our proposed approach. We use the CNN model to predict latent factors of learning resources. As mentioned previously, we convert source learning to text, which will be an input to train the CNN model. In converting operation, firstly, we extract audio from learning video. Then, we used an API from Google to obtain brief text without dropping down in content. Simultaneously, we need to make this automated to perform the speech-to-text transformation. One of the challenges we faced was Google API limitations on audio sequence, so we dealt with this problem programmatically in our source code, keeping the accuracy and content stable. Fig. 4 shows the conversion sequence preferences. Hence, we should regularize the results. So, we will use L1-norm regularization after modifying matrix factorization as represented in Equation 1.

The input of the CNN model will be the language model of the text information regarding the source learning video (output of the previous stage in Fig. 4). Regarding the features of students' preferences and learning videos, we train LFM to extract this information. As we focus on students' historical data, especially on their reviews and comments on learning videos, because free writing text by the user expresses their interests more than the numerical data such as a rating or scoring, for example, one may rate a particular learning video highly but be dissatisfied with the teaching style. That rating number never gives one the area to give their opinion. Hence, we convert all historical reviews using natural language processing (NLP) tools to a rating matrix. The recommendation system rating matrix R is sparse because not all users rate or review all items. We will do our computation in nonempty cells in ratting matrix R (Fig. 5).

Fig. 4 The sequence of the conversion

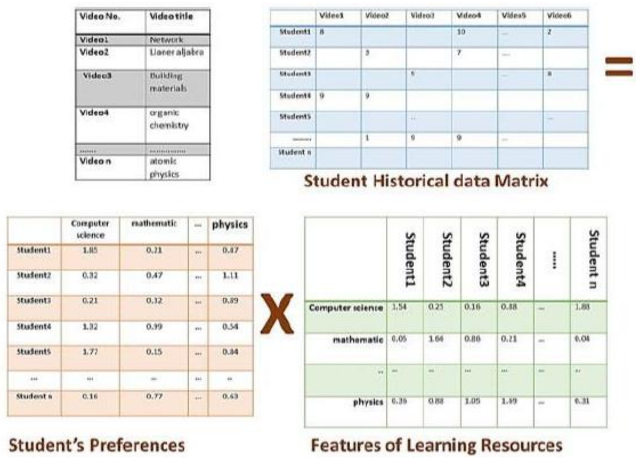

Fig. 5 Process of the latent factor model (LFM)

The latent factor model (LFM) is used to predict learning video features and students' learning interests represented as matrices U and V, respectively. LFM is a model that predicts the scoring between the user and item based on a set number of indirect factors. In addition, it can determine the students' preferences or learning requirements (Fig. 5).

In basic LFM, usually, L2-norm regularization is used to reduce solution space. However, this method may lead to an over-smoothing problem. In our presented framework, LFM results characterize the features regarding the learning videos and users.

$$\boldsymbol{j}(\boldsymbol{U},\boldsymbol{V}) = \sum_{ij}(\boldsymbol{U}_{i*} - \boldsymbol{V}_{*j} - \boldsymbol{r}_{ij})^{2} + \boldsymbol{\lambda}_1\|\boldsymbol{U}\|_1 + \boldsymbol{\lambda}_2\|\boldsymbol{V}\|_{12} \qquad (1)$$

The right part denotes fidelity, and the left parts indicate regularization. U is a matrix referring to the relation between the user and LFMs, V is a matrix representing the relation between learning videos and LFMs, and rij is a symbol referring to a rating by the user with index i of the learning video with index j. As mentioned previously, we applied these computations to nonempty cells in the matrix. Regularization parameters are represented by λ1 and λ2 and needed to balance the fidelity and regularization parts. The L1-norm-based model in Eq. (1) is a non-convex function. To minimize it, to minimize it, GridSearch and cross-validation are used in the parameter optimization part. The proposed recommendation system runs a cross-validation procedure for a given algorithm. Then, a topic model captures this intuition in a mathematical framework.

4. Experiment and Results

4.1. Evaluation Metrics

Three evaluation metrics will be utilized to evaluate the proposed system (precision, recall, and F-measure metrics). In the recommendation process, precision represents the division value of the recommended resource related to the total number of resources (either related or not related) recommended to the students. Recall measure represents the division of recommended resources related to the total number of resources (either recommended or not recommended) related to the students [25]. Equations 2 and 3 show how the two metrics are calculated along with ratings.

$$\text{Precision} = \frac{\text{Relevant recommendations generated}}{\text{Total number of recommendations generated}} \quad (2)$$

$$\text{Recall} = \frac{\text{Relevant recommendations generated}}{\text{Total number of recommendations generated}} \quad (3)$$

The accuracy of recommender systems can be high if the value of these matrices is high. However, sometimes, there is a big number N of recommendations which may increase the recall value and decrease the precision value. Thus, we can use another F-measure metric to reach the best balance between the two metrics. F-measure is computed according to Equation 4.

$$\text{F} - \text{measure} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision Recall}} \quad (4)$$

4.2. Dataset Description

Coursera is the world's largest massive open online course (MOOC) provider and hosts many courses from top universities in different subjects. The data collected 1.45 million course reviews posted by students and participants (https://www.kaggle.com/imuhammad/course-reviews-on-coursera/metadata).

There are two datasets:

1. Coursera courses containing a list of 622 courses on Coursera;

2. Coursera reviews comprising a list of 1.45 million reviews. We abridge the big data set. For testing the effectiveness of cognitive computing techniques, the demonstrative prototype we are going to describe was exploiting videos from three courses:

1. Machine learning from Stanford University at https://www.coursera.org/learn/machine-learning;

2. Python data from the University of Michigan at https://www.coursera.org/learn/python-data;

3. E-learning from University of Illinois Urbana-Champaign at https://www.coursera.org/learn/elearning.

All these are freely available on the website of Coursera for an online learning environment. We have chosen these courses due to the provider's authority and the quality of spoken English. The data sets used in the proposed system are mainly collected in two data files in CSV format. One describes the review data of the users and learning video, which contains 198865 textual reviews and the same number of ratings (from 1 to 5) on 178 videos of the three mentioned courses. The other file contains detailed information about the three learning courses.

Table 1 Dataset course description

Variable	Class	Description
Name	Character	Course name
Institution	Character	The name of the reviewer who wrote the review
Course_URL	Character	Course URL
Course_ID	Character	Course ID

Table 2 Dataset of students' review description

Variable	Class	Description
Reviews	Character	Course review
Reviewers	Character	The name of the reviewer who wrote the review
Date_reviews	Date	Date when the review was posted
Rating	Integer	The rating score given by the reviewer to the course
Course_ID	Character	Course ID

4.3. Simulation Environment

We build our model using Python 3.8.8 on an Anaconda environment and spider on a personal computer with the following characteristics: HP Elite x2 1012 G1, Processor: Intel(R) Core(TM) m7-6Y75 CPU @ 1.20-1.51 GHz, Installed RAM: 8.00 GB (7.88 GB usable), System type 64-bit operating system, x64-based processor. For further video processing and saving, we need to rent a server (GPU dedicated server) from interserver.net (https://www.interserver.net/) company with the following description:

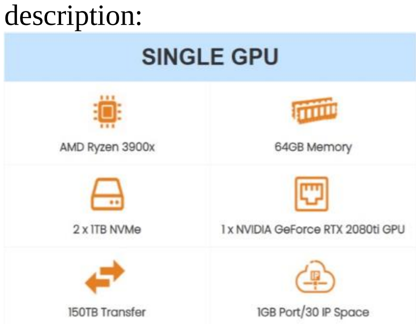

Fig. 6 GPU server configuration

5. Results and Discussion

The prediction we will make is whether the students would like the learning video or not by the brief review of the learning video. There are 198,865 reviews and ratings concerning 178 samples that need to be predicted. Upper bound means the best result we could get, calculated directly with latent factors. Recently we worked on 178 learning videos, which belonged to three online learning courses from the Coursera platform as we described previously.

5.1. Experiment

In the first step we converted all video to text using machine learning tools as previously shown in Fig. 4.

In the first experiment, we converted learning videos to audio. Then, we used Google API to convert speech to text. However, since Google API has limitations for audio length, we broke the longer audio— depending on silence time— into smaller chunks of audio. We then combined all the text into the same audio in a single text file, which will be the input to the next step. We achieved a good result for this stage. For example, for the video entitled "Matrices and Vectors," from a machine learning course on Coursera (accessed by: https://www.coursera.org/learn/machine-learning/lecture/38jIT/matrices-and-vectors), we accessed the text file in Fig. 7.

Let's get started with a linear algebra review. In this video when i tell you what i'm agencies and one of exes. A matrix. Is a rectangular array of numbers written between square brackets. Example here is a matrix. The right let's go back. And then writing a. Bunch of numbers. And you know this could. Features for machine learning problem what could be data from somewhere else. Example the specific values. Don't matter. Close it with another right back it on the right so that's 1 m. 12th. Symmetric is just another way for saying is it 30 or 2 dimensional. Array. Enzyme. Epistemology we need is that dimensional matrix is going to be. Everton has the number of rows. Times the number of columns in matrix. Completely example. This has one too. 34 rose and has. Two columns and cells example the left i'm going to say this is a 4. By 2. Does number of rows by number of columns 0402 harlem. This one on the right this nucleus has to roll that's a first. That's the second roll and has three columns. That's the first column the second column. So. The second matrix crusaders a 253. The dimension of this matrix 2 by 3. Sometimes it also see this written out as. In the kids unless you see the retinal sr4 by 2 countries what's people sometimes say is that. This matrix is an element of a centaur for by to this thing here at this just means he loves all matrices the lot of dimension 4 by 2. And has written out as a matrix present. So give us something like this in your offer by two r23 people just referring agencies of us pacific. Dimension. Next let's talk about how to refer to specific elements of the matrix and by the numbers. So in the standardization is a is this an issue. The 8th of july jay is going to refer to the icon emoji. Meaning. Entry anime traces in the i throw and jfk. Example a11 is it going to refer to the entry in the first row and the first column so that's the first coronavirus column. And so. A11 is going to be good. 14. Barnardo's app. A12. Is going to refer to the entry in the first row. Andy second column. And so they want to. 191.

Fig. 7 Text document result from learning video conversion

Our text file has high similarity to the text description of the video that Coursera provides under each video on the webpage, which can be accessed by the previously listed link (Fig. 8).

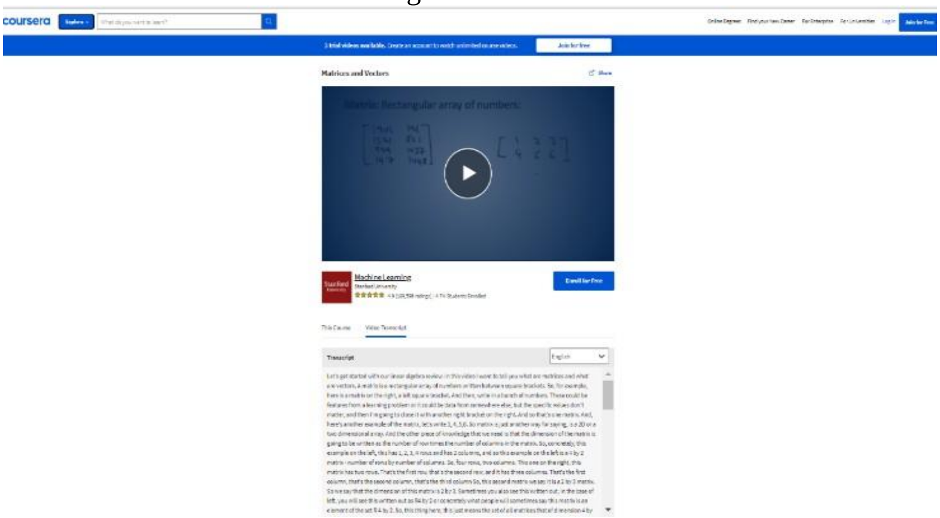

Fig. 8 An example of a video transcript on Coursera site

We used different ways to measure the similarity between our text results and the source text on Coursera, and we compared the results of the different techniques to prove the accuracy of our work. First, we used a natural language processing library named spaCy library, which is written in Python and Cython. We included the spaCy library in our work since research in [26] showed that spaCy is substantially faster than many other libraries. The second method was used to prove that we kept the original content in cosine similarity, which is a basic and effective similarity measure used in conjunction with the TF/IDF weighting scheme [27]. We applied these measurements on different samples of video from our source dataset so that the videos differed in size, length, and type content from the three courses in our dataset (Table 3).

5.2. Discussion

As shown in Fig. 9, there is very high similarity between our text, Coursera's description (original text), and the resulting text. In some short and nonmathematical videos, it matches with 100% similarity. From these result we can conclude:

1. In all 10 videos, spaCy gives higher similarity than cosign. Because spaCy is an integrated library in Python, which we built our model in, there was no loss of information during the computing process;

2. Some videos gave a higher similarity index than other videos in both metrics, which was influenced by the content of the video itself. For example, when the videos have a lot of math, the audio cannot be converted to text with 100% accuracy, because the symbols may be converted to words or formulas may be converted to sentences.

Generally, these results seem to be satisfactory, since all tested videos had more than a 90% similarity index as results confirmed.

Table 3 Description of the tested sample videos

Video	Length (sec.)	Size (KB)	Video title	Course	URL of the Video
Video 1	15:34	32.56	Strings	Python data	https://www.coursera.org/learn/python-data/lecture/HnHCM
Video 2	14:46	31.68	From Didactic Pedagogy to New Learning	E-learning	https://www.coursera.org/learn/elearning/lecture/1jn5i/from-didactic-pedagogy-to-new-learning
Video 3	08:09	19,300	Active Knowledge Making, Part 2A: What Does It Mean to Be an Engaged Learner?	E-learning	https://www.coursera.org/learn/elearning/lecture/PMhtO/active-knowledge-making-part-2a-what-does-it-mean-to-be-an-engaged-learner
Video 4	09:18	17,49	Ubiquitous Learning, Part 1A: Learning in Space and Time	E-learning	https://www.coursera.org/learn/elearning/lecture/aUuGe/ubiquitous-learning-part-1a-learning-in-space-and-time
Video 5	10:40	12,14	Regularized linear regression	Machine learning	https://www.coursera.org/learn/machine-learning/lecture/QrMXd?t=90
Video 6	08:45	9,73	Matrices and vectors	Machine learning	https://www.coursera.org/learn/machine-learning/lecture/38jIT?t=514
Video 7	06:53	7,63	Addition and scalar multiplication	Machine learning	https://www.coursera.org/learn/machine-learning/lecture/38jIT?t=514
Video 8	00:38	6,75	Fun Python Lists in Paris	Python data	https://www.coursera.org/learn/python-data/lecture/gynni/fun-python-lists-in-paris
Video 9	04:22	6,20	Macintosh: Using Python and Writing A Program	Python data	https://www.coursera.org/learn/python-data/lecture/BwsVs/macintosh-using-python-and-writing-a-program
Video 10	03:17	3,85	Unsupervised learning introduction	Machine learning	https://www.coursera.org/learn/machine-learning/lecture/olRZo/unsupervised-learning

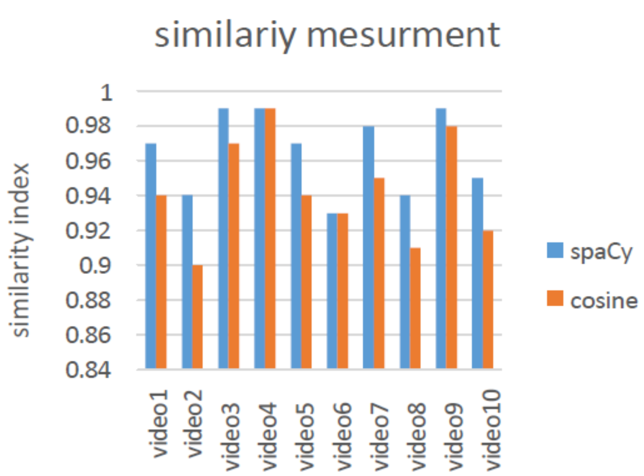

Fig. 9 Similarity index using spaCy and cosine measurements

6. Conclusion

Video learning became the most important learning resource in all eLearning activities. Hence, it provides all information and is easy to understand and track, in addition to the ability to control (repeat, puss, forward, and backward), which gives the learners comfortability to learn and save time and effort. Nonetheless, using video as a learning resource is a good eLearning methodology. It is already used on many platforms. So we need to improve the way we deliver learning video resources when learners access learning videos based on their learning interests. There is a need for a good recommendation system to deal with a large number of delivered resources and learners' requirements, leading to a new generation of adaptive eLearning platforms. This article presents a content-based framework for learning video recommendations based on a convolutional neural network and students' reviews of learning videos. The proposed technique is tested on a real-world dataset. In this article, we build the theatrical model and prepare the training model by justifying its input and output. In the next extended versions of this paper, we will display and discuss the rest of the results of the practical model, on which we still work to obtain good results. We will work on analyzing users' comments, including punctuation, conjunctions, emoji, slang, and emoticon, and train our model to retrieve the most recommended videos. In the future, we intend to use a transformer network to train a recommendation system that will enhance the model performance [28]. We must solve its limitation of long text sequences allied to a learning video.

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