Supporting Online Video Learning with Concept Map-based Recommendation of Learning Path

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Abstract
People increasingly use online video platforms, e.g., YouTube, to locate educational videos to acquire knowledge or skills to meet personal learning needs. However, most of existing video platforms display video search results in generic ranked lists based on relevance to queries. These relevance-based information display does not take into account the inner structure of the knowledge domain, and may not suit the need of online learners. In this paper, we present ConceptGuide, a prototype system for learning orientations to support ad hoc online learning from unorganized video materials. ConceptGuide features a computational pipeline that performs content analysis on the transcripts of YouTube videos queried by the user and generates concept-map-based visual recommendations of conceptual and content links between videos, forming learning pathways to provide structures feasible and usable for learners to consume.

Author Keywords
Education/Learning; Information Seeking & Search; Visualization; Concept map

Introduction
As the development of the Internet has reached the states of maturity and stability, people now may start to access professional educational content on specialized online learning platforms such as MOOCs and open courseware,

or video-sharing platforms, such as YouTube.Generic video-sharing platforms like YouTube have provided a flexible and liberal medium for knowledge sharing and a mode of education [9, 18], where there's no or little cost for teaching and learning.

Compared to typical lecture videos on MOOCs with a classroom-education-like form and structure of teaching, a large part of YouTube learning videos tend to be less formal and also rather independent of other video contents from the same query. Since there is little limitation about video uploading, learning materials available on YouTube are likely to be more diversified in terms of genres, aspects, scopes and also quality when comparing to MOOCs. Therefore, without systematic guidance and support, learners may encounter difficulties in seeking appropriate educational videos on YouTube. A certain level of background knowledge is likely needed if learners want to find, filter, and organize the video materials obtained [7]. Also, they need to find appropriate video sequences to understand basic and advanced concepts in a good order. Novice learners thus tend to face a paradoxical situation where they need the domain knowledge they don't have in order to consume information available in a generic video archive like YouTube [16].

To deal with the aforementioned issues in content accessibility and consumption, we noted the potential utility of concept map visualization, which were originally applied as a strategy for visual learning and assessment [3, 11]. A concept map visually organizes and represents knowledge as a graph, of which nodes are concepts and links denote relations between concepts. Previous studies have shown that concept maps can provide a simplified representation of a domain and may selectively focus on key concepts of the domain to support learners [12].

By offering an overview of learning contents and showing prior or further concepts to learn, concept maps were also found to help learners locate their current context and reduce the feeling of disorientation [3, 6].

In this paper, we present a system prototype, ConceptGuide, that supports learning from YouTube videos, especially for those who are novices in a topic (see Figure 1 for a screenshot of ConceptGuide). After users enter a topic (keyword) to learn, the video search results are visually represented in a concept-oriented graph visualization. Users can actively explore relationships between concepts and learning sequences of concepts, check and watch their corresponding videos and visually explore previous viewers' feedback through the visualization. And they can also follow our path recommendations for both exploratory and in-depth learning. The system also provides users with multiple, diverse video options for one concept.

Related Work

Interactive and Visual Tool for Online Learning

Many approaches have been proposed for visual analysis of educational data in order to improve students' learning efficiency, e.g., various visual designs for preview videos to help users navigate through an instructional video [21, 10, 5]. Their visualization contents include integration of textual, visual and audio information, multimedia exercise, and keyword summary. On another line, some research focused on improving learners' searching efficiency from multiple educational videos or pools. Optical character recognition technology was considered in the search engine to find appropriate content [1]. Personal profile and learning needs were analyzed for the recommendation of course from MOOCs [2]. However, the research aforementioned focused on finding and supporting single video. There are very few works to support the learning of a series of videos, which is crucial for online learning as single videos cannot cover everything.

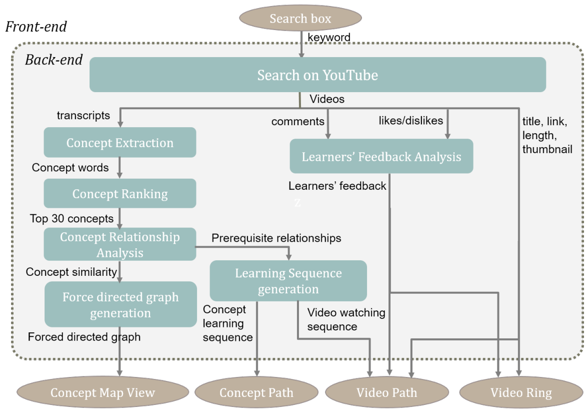

Figure 2: Overview of concept map construction

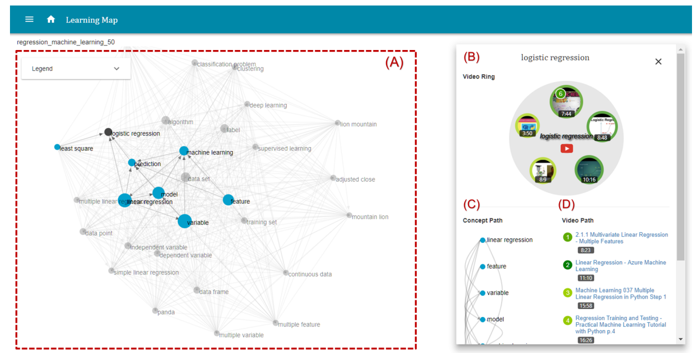

Figure 1: Overview of ConceptGuide. It provides Concept Map (A), Video Ring (B), Concept Path (C), and Video Path (D) to learners. ConceptGuide shows basic concepts and concept map for the keyword searched (“logistic regression” here) by organizing video searched from YouTube interface. When the mouse hovers over one concept, a pop-up window shows most relevant videos to the concept or subtopic (B), a recommendation path for learning the concept and its prerequisites (C) and the corresponding video recommendation path (D).

Concept Map Construction

Concept map is a well-known and widely used tool in education. It provides a visual representation to denote concepts and inter-concept relations as a human-comprehensible graph. Shaw's work [17] shows that learning efficiency can be improved and knowledge can be better acquired by learners with the concept map representation. Research interest in automatic concept map construction has grown in recent years. Several techniques studied extracting useful features from educational data to build concept maps, including TF-IDF, LDA, and extra information from Wikipedia Glossaries [20, 22]. However, there hasn't been much work on proposing an integrated computational workflow for extracting concept maps from unstructured videos in the context of online learning.

System Prototyping for ConceptGuide

System Overview

ConceptGuide provides keyword-driven interactive navigation of video contents for learners to explore videos uploaded on YouTube, as shown in Figure 1. It automatically searches YouTube videos based on a queried keyword and returns a concept map by analyzing video transcripts, along with recommended videos and suggested learning sequences according to the relevance of the keyword to associated concepts in the map, quality of videos, and previous learners' feedback commented on the video on YouTube. As shown in Figure 1, ConceptGuide provides four views on its interface: (A) Concept Map, (B) Video Ring, (C) Concept Path, and (D) Video Path.

Interface and Visualization Design
For an input query, a **Concept Map** is constructed from top YouTube videos by using a system workflow that we'll describe later. We apply the force-directed graph [4] to visualize the map. Each node in the concept map presents a concept and its radius implies the term frequency of the concept. The edge distance between two nodes is inversely proportional to the similarity between the two nodes (concepts). When users hover over a concept (e.g., "logistic regression" in Figure 1(A)), its prerequisite concepts are highlighted in blue and solid arrows for recommended learning path. If users further click on the node on the Concept Map, a pop-up window with Video Ring, Concept Path, and Video Path displays more detailed information and learning suggestions.

Video Ring (Figure 1(B)) visualizes the videos that introduce the clicked (selected) concept with rich information, including the frequency of the concept appearing in the video and previous viewers' feedback. **Concept Path** (Figure 1(C)) is a short summary of the selected concept and its related ones. It only maintains prerequisite related concepts. The gray lines show the prerequisite relationship between concepts.

Video Path (Figure 1(D)) specifies the videos for a Concept Path. Since each video usually includes multiple concepts, we arrange the the videos in an order that best follows the concept path for better learning performance. Users can hover over a video to check their corresponding concepts (highlighted) in this part. Moreover, the background colors of the order number represent the video's sentiment: green means positive, and red represents negative. TextBlob [13], a natural language processing toolkit in Python, was adopted in our system to analyze the sentiment of comments.

Concept Map Construction
Figure 2 shows an overview of the construction of concept map. ConceptGuide collects the videos and transcripts as materials from YouTube [19]. Moreover, the comments and the number of likes/dislikes of each video are used to analyze the sentiment of learners' feedback, which may imply the quality of a video. ConceptGuide also utilizes other video information such as thumbnails, links, duration, and title, to present the concept map and recommend learning path and video ring in the interface.

Concept Extraction
We first applied rapid automatic keyword extraction (RAKE) algorithm [15] to collect keywords directly from transcripts. RAKE determines keywords based on the frequency of word appearance and its co-occurrence with other words in the document. When applying RAKE to learning videos in our case, we solved two semantic meaning issues: detection of domain-specific keywords and polysemy identification. Furthermore, inspired by Wang et al. [20], we applied Wikipedia glossaries to filter out irrelevant keywords from RAKE results. Wikipedia glossaries include key concepts which have Wikipedia pages in the same domains, which implies the importance of these concept words. And they are well organized and accurate. Our system adopted 37 different Wikipedia glossaries that cover most basic fields of science, including architecture, calculus, chemistry, history, etc. To better select the domain-specific words and solve the problem of polysemy with Wikipedia glossaries, we applied Google Cloud Natural Language (Google NLP) API to detect videos' domain [8], which analyze the document and return a list of content categories that apply to the text found in the document.

Besides the transcripts, we also used the tags of the YouTube video to extract concepts. They often contain useful information of video from the perspective of uploaders, such as subject areas, themes, and key concepts.

We also designed five features to select the most important concepts from the long list. Features *Tf* and *NumOfVideos* consider the occurrence of a concept in videos. A concept which frequently appears in videos is more important. *MaxTfidf* is adopted because of its meaningfulness for individual videos. Video's title is often the most important information. Thus, we emphasize the importance of a word if it appears in a video's title (feature *IsInTitle*). Furthermore, proper nouns often appear with two or more words, so we take *IsMultiWords* into account. All of these features are normalized to range [0, 1] and their weights are tuned.

Concept Relationship Analysis

To construct the concept map, the relationships among concepts, including their similarity and prerequisite were analyzed. We used the N-gram method to form concept vectors for semantic distance: similar concepts are close in the vector space. And prerequisite relationship decides the direction of learning path. Below we describe how concept similarity and prerequisite relationship are computed.

Concept Similarity. To measure the similarity between two concepts, we consider both local and global similarity from the co-occurrence of the two concepts in the same video and in Wikipedia. It's measured as the sum of cosine distance of two concepts in the videos and their reference existence in Wikipedia.

Prerequisite Relationship. We adopted four of the seven concept features proposed by Pan et al. [14] to infer the prerequisite relationship between concepts. These features are slightly modified to better fit the YouTube video environment. These features described below cover semantic, contextual, and structural aspects of relationship.

Semantic relatedness (Sr) is defined as the same as *concept similarity*. *Video reference relatedness (Vrr)* was directly adopted from [14]. It calculates the co-occurrence term frequency of concepts in videos. Pan et al. observed that basic concepts are mentioned more frequently in the videos of earlier lectures while advanced ones are seldom mentioned in earlier lectures. *Wikipedia reference relatedness (Wrr)* is selected due to the similar reason of *Video reference relatedness*. Basic concepts are mentioned more often in the Wiki pages of advanced concepts. *Complexity level distance (Cld)* considers average video coverage and average survival time of a concept. A basic concept is more likely covered in more videos or survives longer time in a course than the advanced ones.

Finally, the relationship score $P(a, b)$ between two concepts a and b is defined as the weighted sum of normalized value of the four features. If $P(a, b) > 0$, a is b's prerequisite; if $P(a, b) < 0$, vice versa.

Experiment and Preliminary Results

Experiment

To evaluate the performance of ConceptGuide on learning assistance, we conducted a within-subject experiment. We invited 16 participants to learn new topics on both YouTube (C1) and our ConceptGuide system (C2). Each participant was instructed to complete learning tasks in YouTube and ConceptGuide, respectively. To prevent the influence of learning effect, systems and learning tasks are counterbalanced. The two learning tasks were searching and watching related videos to learn knowledge about "Bitcoin" and "Natural Language Processing", respectively. We designed a pre-test and post-test for learning outcome assessment, surveyed participants with a questionnaire and interviewed them to understand their experience of use. The browser history was also recorded for analysis.

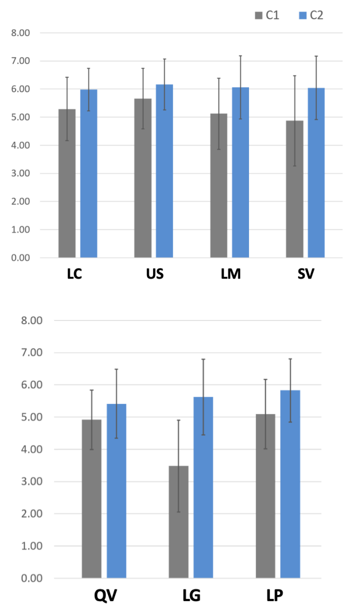

Figure 3: Learning self-evaluation on using Youtube (C1, gray bars) and ConceptGuide (C2, blue bars). ConceptGuide was significantly better than YouTube in all aspects of evaluation, including learning concentration (LC), usability of system (US), learning motivation (LM), scope of videos (SV), quality of videos (QV), learning guidance (LG), and learning performance (LP) (from left to right). The error bars represent the standard errors of scores.

Analysis and Results

Figure 3 shows the results of the questionnaire. They represent participants' evaluations about ConceptGuide. Repeated-measure ANOVAs found that the mean scores of ConceptGuide (C2) were significantly higher than YouTube (C1) in all aspects of evaluation, including learning concentration, usability, learning motivation, scope of videos, quality of videos, learning guidance, and learning performance. Combined with corresponding interview feedback, results about learners' experiences with ConceptGuide are reported here. Participants reported positive feedback from the perspective of learning concentration, guidance and learning confidence.

Learning concentration. The concentration score of C2 (M=5.979, SD=0.5640) was significantly higher (F(1,15)=4.543, p=0.0083) than C1 (M=5.292, SD=0.7084). In the interview, five participants reported they were more concentrated on learning in C2 than in C1. Four of them mentioned that high content overlap of videos in C1 caused them getting distracted at the middle of the task. Another participant reported she got distracted in C1 because of her discontent about the videos.

Learning guidance. The average scores of C1 and C2 were 3.484 (SD=1.171) and 5.625 (SD=1.004), respectively. The score of C2 was also higher (F(1,15)=4.543, p=0.0001) than C1. Almost all participants (N=14) agreed that our ConceptGuide system helped them learn more systematically. They could keep finding unknown concepts they never heard, and found related videos with more clues. Fifteen participants also mentioned that in C1 they were perplexed for the videos they should watch next sometimes, due to the high overlap of videos. With the help of our system, search efficiency was highly improved. These feedbacks resonate the point of view that structural visualizations offered can guide learners to explore the conceptual space more efficiently.

Learning performance. Participants generally felt that they learned better using ConceptGuide (F(1,15)=4.543, p=0.0106). About half participants (N=7) reported that they learned better in C2 because of the overview and step-by-step guide. It was helpful for them to check whether there were any missing concepts in the map, thus they were more confident about the integrity of learning. ConceptGuide system supports their learning confidences from obtaining constructive learning experiences.

Future Work

We will continue the analysis of experiment, including a learning efficiency analysis. We also consider adding personalized recommendation into the system when richer usage data become available. Users may also participate in the construction of concept map. The existing browsing history we have along with past recommendation would be a good resource to guide future learners' personal learning paths.

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