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From Ideal to Reality: Segmentation, Annotation, and Recommendation, the Vital Trajectory of Intelligent Micro Learning

Jiayin Lin
University of Wollongong, jl461@uowmail.edu.au

Geng Sun
University of Wollongong, gsun@uow.edu.au

Tingru Cui
University of Wollongong, tingru@uow.edu.au

Jun Shen
University of Wollongong, jshen@uow.edu.au

Dongming Xu
d.xu@business.uq.edu.au

See next page for additional authors

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Authors

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Jiayin Lin[1], Geng Sun[1], Tingru Cui[1], Jun Shen[1,2], Dongming Xu[3], Ghassan Beydoun[4], Ping Yu[1], David Pritchard[2], Li Li[5], Shiping Chen[6]

[1]School of Computing and Information Technology, University of Wollongong, Wollongong, NSW, Australia
[2]Research Lab of Electronics, Massachusetts Institute of Technology, Cambridge, MA
[3]UQ Business School, The University of Queensland, Brisbane, QLD, Australia
[4]School of Information, System and Modelling, The University of Technology Sydney, NSW, Sydney
[5]Faculty of Computer and Information Science, Southwest University, Chongqing, China
[6]Data 61, CSIRO, Sydney, NSW, Australia

jl461@uowmail.edu.au, {gsun, tingru, jshen, ping}@uow.edu.au, d.xu@business.uq.edu.au, ghssan.beydoune@uts.edu.au, dpritch@mit.edu, lily@swu.edu.cn, shiping.chen@csiro.au

Abstract

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Keywords— micro learning, video segmentation, automatic annotation, recommender system, machine learning, data mining

1 Introduction

The soaring development of the Internet and mobile devices catalyse the evolution of the mobile application and service. Such development breaks the time-space restriction, and make it possible that people can work, entertain, and study at almost anytime and anywhere. In the meanwhile, due to the fast-pace of modern life and immerse usage of mobile devices, people's spare time is split into irregular small time slices between the switch of different activities. After entertainment industry firstly starts mining the great value of user's fragmented time, researchers in the area of technology-enhanced learning (TEL) start to investigate how to make good use of such small chunks of time to carry out effective learning activities.

As discussed in our prior study [1], to fit the user's fast-paced lifestyle and satisfied the life-long learning requirements, it is necessary to deliver users small adaptive chunks of learning materials. These small chunks of learning materials are supposed to be learnt in relatively short and isolated time durations. The term 'micro learning' used in this paper refers to the service that generates and provides users personalized small chunks of learning materials. As found in the studies [2, 3], user's engagement of online learning activities plunge quickly after 7 minutes, and videos with short time duration are more popular among learners. Moreover, as pointed out in the study [4], for a short learning session such as a short video, users are less likely to leave out the knowledge points. Hence, the micro learning service, which aims to make use of user's fragmented time and offer personalized small chunks of learning materials, has great potential in fitting fast-paced lifestyle and alleviating engagement issues.

Serving as the extension of our previous literature review [5], in this paper, we surveyed a wide range of potential solutions for segmenting and annotating online learning materials; we also reviewed many novel recommendation strategies for e-learning scenarios. For the technical part of each micro learning processing stage, there exist many literature reviews respectively. However, there are still lack of the reviews which completely discuss the whole workflow of a micro learning system. On the other hand, as a large proportion of online learning materials are in the video format, the discussions and analyses in this paper are mainly based on the video-format learning materials.

The remainder of this paper is organized as follow. In Section 2, before diving into the technical details of each processing stage, we firstly introduce the proposed framework of a micro learning system and describe the utility of each vital component of the system. Then, we discuss and compare the details of the reviewed studies about the segmentation and annotation strategies in Section 3. The state-of-the-art recommending strategies are discussed and analysed in Section 4. In Section 5, we summarized and highlight the current challenges and research gaps in the area of micro learning. We conclude this paper and pinpoint the future work in Section 6.

2 Proposed Micro Learning Framework

The delivery of intelligent 'micro learning' is an online learning service, which aims to offer users small chunks of personalized learning materials. The workflow of an intelligent micro learning system can be separated into two decision-making procedures: the transformation of non-micro learning materials to micro learning materials, and the recommendation of personalized learning material. In this section, we outline the proposed workflow as depicted in Figure 1.
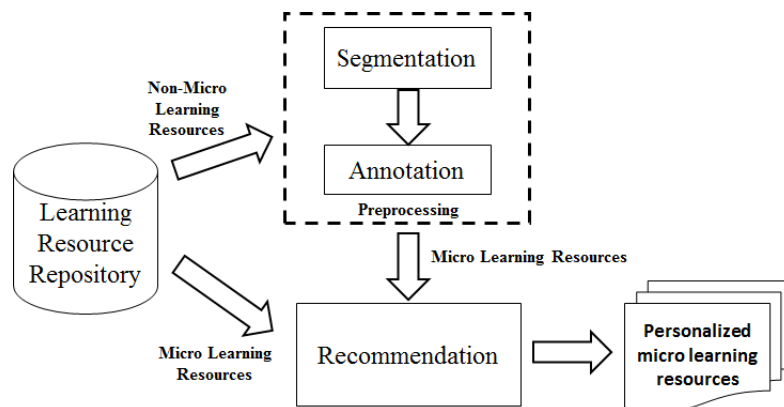

Figure 1. The Workflow of a Micro Learning System

2.1 Learning materials Pre-processing

As mentioned in [1], the time length of many online learning materials is greater than 15 minutes, especially the lecture recordings in the various learning management system (LMS). We regard these aforementioned learning materials as non-micro learning resources. Such non-micro learning materials should be logically segmented, and each segmented unit should include a coherent knowledge point or sub-topic of the original material. Prior studies pointed out that segmented learning materials could offer a more flexible and non-linear learning path [6], and enhance the accessibility of learning resources [7]. The output of the segmentation stage is in the format of fragmented knowledge points without any descriptions. The content of these knowledge points are vague due to lacking descriptive metadata such as the title and descriptions. Hence, an annotation stage is required to make the segmented learning units ready for delivering to users.

2.2 Learning materials delivery

In the big data era, the explosive growth of data on the Internet floods users with tremendous information in both volume and complexity. Such information overload requires an intelligent module, which can automatically filter out unsuitable information and then select the most suitable one for users. The task of learning materials delivery is to recommend personalized micro learning material to a target user based on

his/her preference, learning requirements, learning history, etc. As argued in[8], in an online learning scenario, it is difficult for a user to choose the suitable resource for himself/herself without sufficient background knowledge.

3 The Pre-processing Stage: Segmentation and Annotation

Term 'micro' is the innovation point of such online learning service, which focus on utilizing learners' small chucks of spare time and helping learners acquiring knowledge piece by piece. Segmentation and annotation are two vital processing steps in the pre-processing stage which guarantee the generating micro learning materials from non-micro ones and making micro learning materials ready for delivering.

3.1 Segmentation

Intuitively, based on the type of information used in the segmentation process, segmentation strategies can be categorized into two classes: content-based and user-interaction-based. The former category does not require too much user-side information, such as user's historical learning records, but often relies on state-of-the-art and cross-domain machine learning models such as Optical Character Recognition (OCR) and Automatic Speech Recognition (ASR). The latter category is more light-weight compared to the first one; in most cases, the model is based on the demographic information and does not interpret the content of learning materials. But it is very critical to note that both strategies are data-driven; in other words, no matter what strategy will be applied for learning material segmentation, it is always necessary to mine and interpret the hidden information. The summarization of the reviewed segmentation strategies is shown in upper part of Table 1.

3.1.1 Content-based Segmentation Strategy

Generally, for the micro learning service, content-based segmentation strategy focusing on interpreting the content information of multimedia learning resources and then locating the boundaries of each knowledge points. As the types of the online learning resource varies greatly, for different types of multimedia resources, such segmentation strategy requires different techniques to interpret the content information and locate the boundaries.

Table 1.   COMPARISON OF ANNOTATION STRATEGY

Processing Stage	Category	Highlights	Limitations
Micro Learning Resource Segmentation	Content-based [6-15]	Does not need user-side contextual information.	Often requires the state-of-the-art and cross-domain machine learning algorithms. In some situations, OCR and Automatic Speech Recognition (ASR) could be error-prone [9-11].
	User-interaction-based [16]	No need to analyse the content of learning materials.	Similar to the crowd-wisdom based annotation strategy, it is sensitive to the cold-start problem, and user interaction could be noisy and unreliable.
Micro Learning Resource Annotation	Ontology-based [22]	Theoretically it can model and represent any relationships between two learning resources.	The construction of the ontology model is very time consuming and labour intensive. Moreover, ontology-based model requires all the resource strictly follows a standard formation which is hard to achieve in an open learning environment.
	Crowd-wisdom-based [19, 25-29]	It is light-weight, easy to implement and could offer the additional information about learners at a finer scale.	This method is very sensitive to the cold start problem as it takes time to collect user feedback. This method might also face the convergence problem. When using this strategy researchers should make sure that the result will convergence for a certain time period, especially in the open learning environment.
	Model-based [30-33]	This strategy mainly refers to the machine learning and data mining models which based on solid mathematical theories, it is robust.	As the online learning environment is dynamic, the model needs to be updated after every certain time period.

Accurate detection of the boundaries from a video stream is the key for an effective segmentation method [7, 9]. A conventional boundary detection method of video stream is based on the difference in colour histogram of frames; when the scene transitions occur, such difference in colour histogram between two different scenes is significant. However, in the educational domain, due to the non-significant difference of colour histogram between two different knowledge points, this boundary detection method is error-prone. For example, as indicated in [10], usually the slides of one lecture video are all similar to each other because a single template is used to produce them. Authors of [11] argued that two different slides could have almost exactly the same colour histograms.

To differentiate the lecture slides in one video, some studies [10, 12] utilized the difference of the black pixel distribution to capture the boundaries of topics. The authors argued that for different topics, slides might have different text content; and these differences would influence the distribution of the dark pixels. Despite the low-level content information such as colour histogram and pixel value, as highlighted in [13], text displayed in a lecture video contains important information about the video content. Extracting textual information for video learning material segmentation is a vital stage in many prior studies [10, 11, 13-15]. The off-the-shelf Optical Character Recognition (OCR) and Automatic Speech Recognition (ASP) engines make extracting textual information from video become possible. Due to different scenes such as slides, the background, and the instructor are blended together in many videos, after extracting textual information, OCR is also used to distinguish the different scenes and regions from keyframes [10]. In two other studies [13, 15], after extracting the textual information, the difference of connected components between two frames were analysed for detecting the segmenting points.

Researchers used Support Vector Machine (SVM) and Nature Language Processing (NLP) strategies to automatically segment the lecture videos in [16]. Text information and video information were both extracted before the final segmentation stage. As discussed in this study, this hybrid method could solve some non-ideal cases when video information was solely used, such as when lecture videos were recorded with a single shot, or when the slide transitions occurred between two slides without any other changes in the background [16]. In addition, using the N-gram model, semantic information could be reserved, and the key phrases could be easily extracted and used as annotations for each segmented video.

3.1.2 User-interaction-based Segmentation Strategy

As a more lightweight strategy, user-interaction-based segmentation strategy refers to the one that is mainly based on the demographic information from users' historical learning activities such as online watching behaviours, which is an indirect segmentation strategy and does not require much content information of the learning resources.

As indicated in [17], peaks in re-watching sessions and play events indicate points of interest and confusion. These pints of interest and confusion can offer useful demographic information for detecting the boundaries for learning materials segmentation. Moreover, [17] also concluded the five activities categories that could cause a watching peak, and more than 60% of the peaks were accompanied with visual transitions. A visual transition in a lecture video is typically a potential indication of a topic change.

3.2 Annotation

As mentioned earlier, most segmented video units do not contain any descriptive metadata; an annotation step is required to make micro learning resources both machine-understandable and human-understandable. In short, after segmenting, descriptive information should be automatically generated to make segmented units interpretable. As discussed in many studies [18-21], proper annotation, indexing, or tagging are essential for searching, retrieving, aggregation, recommendation, and reusing of resources. According to [18], the annotation is essential for the accessibility as well as the sharing and reusing of educational resources; the non-indexed resource cannot be found and therefore, is hard to be reused [22]. Generally, annotation strategies can be classified into three categories: ontology based, model based, and crowd-wisdom based. The summarization of the reviewed annotation strategies is shown in bottom part of Table 1.

3.2.1 Ontology-based Annotation Strategy

With the strength of describing deep semantic information, ontology or 'linked data' can be used to construct and formalize the concepts of a certain domain, and describe the mutual relationships between learning resources. Theoretically, such annotation strategy can directly model any complex relationships and describe the semantic information between two micro learning resources. However, the construction of ontology-based annotation model is always labour intensive. For developing ontology-based model, due to lacking efficient and mature methods for relationship mining and metadata generation, most of these procedures are still based on manual operations and relying on expert domain knowledge [23]. Furthermore, in an open learning environment, learning service may be under a mixture of formal, informal and non-formal learning scenario, which makes it impossible to guarantee that every single uploaded resource strictly follows the same requested standard format such as learning object metadata (LOM) [24], Dublin Core [25], etc.

3.2.2 Crowd-wisdom based Annotation Strategy

Apparently, the explosive growth of data makes manually annotating online learning resources becomes impractical. For micro learning, segmenting non-micro materials will automatically generate countless micro learning units. Many prior studies [20, 26-30] proposed to let user annotate learning materials, then summarize the demographic information and reuse the annotated results. [27] proposed a folksonomy where researchers let users annotate the important points of a lecture video by simple button-press interaction during the learning activities. A histogram about the important points of a given video was therein generated based on the summarization of users' button-press interaction. Another example of folksonomy was directly letting users add tags to the learning resource as in [26]. Moreover, as pointed out in two previous studies [27, 28] that the annotation process and results of each learner offered an additional fine-grained source of information for learning analytics. The annotation results can also partially reflect the cognitive level and the learning outcomes of each learner.

However, in most cases, a crowd-wisdom based annotation strategy is in an open setting, which means there is little or no restriction for an annotation process and a user can annotate the learning materials freely. As discussed in [19], without the restriction of verbalism of the tags, the vocabulary of tag might grow infinitely with the user's interactions. Hence, it is necessary to make sure that for a crowd-wisdom-based model the annotation result for a specific micro learning resource will converge after a certain period of annotation procedure.

3.2.3 Model-based Annotation Strategy

Model-based annotation strategy refers to utilizing data mining and machine learning models to extract relevant content information and annotate learning resources. NLP technologies are essential for extracting, analysing, and summarizing online resources as most of them contain textual metadata like title and description. However, for the micro learning service, the content of a learning resource could be in video, text, or audio format. Hence, many studies [26, 31-34] heavily relied on their annotation strategies on OCR and ASR techniques. In these research works, non-textual information was firstly transformed to textual counterparts, then NLP techniques were applied for the following annotation process.

Moreover, despite the exact content information of the learning resource, many educational learning resources have a similar organization pattern. Such pattern could offer valuable information for identifying the key terms during the annotation process. As discussed in [18], learning resources have a specific structure, which characterizes them from all other types of online resources. For example, many lectures follow specific didactic patterns, such as starting with an introduction, consists of serval subtopics, and ending with a conclusion. The study [33] proposed a novel idea to index and annotate the educational video. The authors argued that the organization of the video content could be modelled by a state model, like the Hidden Markov Model (HMM).In many actual cases, a lecture video did start with a course outline; and for each topic, it was more likely it started with a definition and less likely with a discussion. Similarly, based on the structure information of learning materials more weight was put on the terms extracted from the titles and sub-titles [16, 18, 32].

4 Information Delivery Stage: Recommendation

As the key to personalization, a recommender system, to a great extent, determines what kind of information will be finally delivered to the users. A good recommendation strategy should have the ability to automatically adjust the type of information to be delivered based on the user's background and the surrounding environment of the current learning activity. Compared to the other domains like e-commerce or entertainment, a recommending task in the educational domain has several unique characteristics and requirements:

1. Learning activities and learner profiles always contain vague and uncertain information [35]. A subject can belong to several different categories. For example, a subject 'statistical machine learning' is mainly relevant in computer science area but also involves mathematics. Sometimes similar courses have totally different names such as 'Java' and 'Object-Oriented Programming'. And for a subject, it can have different difficulty levels for learners with different knowledge levels.
2. Pedagogical issues also influence recommending procedures significantly [35]. Items liked by certain learners might not be pedagogically appropriate for them [36]. Unlike the recommender systems in the entertainment or social media domain, in the educational area, many subjects have various prerequisite

Table 2.   COMPARISON OF RECOMMENDATION STRATEGY

Functionality	Techniques	Highlights	Limitations
Sequential Modelling (Learning Path Optimization / Design)	Swarm Intelligence [38, 39]	An unsupervised method, which only requires users' learning history.	It is very sensitive to the cold start problem as it requires predefined paths at the initial stage of the algorithm.
	Reinforcement Learning [56]	Learning gain of reinforcement learning can be simply represented quantified by the accumulated score during the learning activities.	However, not all online learning activities or platform involve a scoring system to track the performance of online learners. Without the scoring system, researchers should try to find another way to represent the accumulated gain during the learning activities.
Object Representation (User / Item Modelling)	Swarm Intelligence [40, 46]	A novel optimizing strategy, sometimes it outperforms conventional weighting strategy. Compared to GA, PSO requires less computational time and more accurate.	Due to its bio-style optimizing method, it is very computational time expensive.
	Evolutionary Computing [41, 42, 44, 45]	A novel optimizing strategy, sometimes it outperforms conventional weighting strategy. It is able to explore new features in the global area with a smaller training set.	
Uncertainty Representation and Modelling	Fuzzy Set [34, 36, 40, 41]	Shows satisfactory performance in handling the incomplete or imprecise information, which is very significant in modelling a real-life problem.	But in some situations, it requires many predefined rules to make decisions.
Data Supplementation (Alleviating Insufficient Data / Offering Supplementing Information)	Transfer Learning [49-52]	Transfer learning works well with insufficient and unlabelled data. And it shows potential to alleviating the data insufficiency problem.	It is hard to identify and verify the effective auxiliary (source) domain, and there is no guarantee that different domains share same user/item latent information or patterns.
	Contexture-aware Recommending [65-69]	Context-aware recommending can differentiate different users within different contexts, which it an important idea for personalized learning	Due to tons of features and relevant information involved in a learning activity, it requires feature engineering and domain knowledge to pick out the suitable contextual features.

courses. Also, for a certain period of learning, a review or quizzes always need to be involved for the pedagogical purposes.

3. As the micro learning units vary in type (such as lecture, quiz, and tutorial) and format (such as PDF, video, and audio) [37], recommending process should also consider how to choose the most suitable format and type of a learner based on a different context.

Base on the previous research [38], the conventional recommender system (RS) can be categorized into three classes according to which techniques are applied and what type of data is used: content-based filtering (CB), collaborative filtering (CF), and hybrid recommending strategy. However, due to several unique requirements and characteristics we mentioned above, these conventional recommendation strategies cannot fully satisfy the requirements of personalized real-time and micro learning. In the following sections, we discuss and analyse several representative novel recommending strategies, which could show great potential to boost the recommending result and alleviate different challenges. The summarization of the reviewed recommendation strategies is shown in Table 2.

4.1 Soft Computing

Soft computing techniques show fairly immense potential for modelling the uncertainty of the real-life problem, which can provide robust, effective, and general predictions in the 'Big Data' context. One prior study [38] mentioned that soft computing could boost the conventional recommendation strategies. Generally, soft computing techniques can be categorized into four categories: fuzzy set, artificial neural network (ANN), evolutional computation, and swarm intelligence [38], as shown in Figure 2. As there are many existing surveys on neural network, this paper will only focus on discussing the fuzzy set, evolutionary computation, and swarm intelligence.
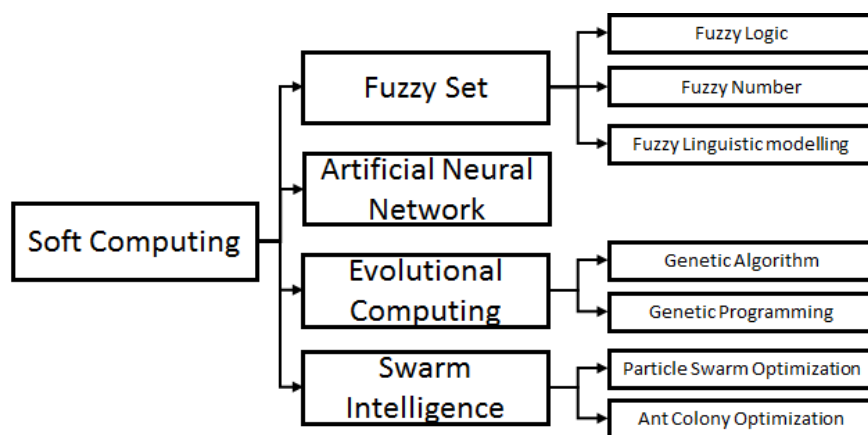
Figure 2. The Category of Different Soft Computing Techniques

4.1.1 Soft Computing for Modelling Uncertainties

Introduced by Lotfi Zadeh, fuzzy set shows satisfactory performance in handling the incomplete or imprecise information. In [37], authors proposed a neuro-fuzzy inference system for recommending the most suitable format of educational material. The features involved in this model were mainly based on the properties of devices and the surrounding environments, such as location, network bandwidth, and battery life. In another study, researchers used a fuzzy tree-structure-based model to represent the organization of information [35]. The authors maintained that learning resources and learners' profile were presented in a tree structure in many e-learning platforms, such as a tree-structured course category system. In their work [35], tree nodes were represented as fuzzy sets, the similarity between item-item, user-user, and even item-user could be calculated based on the operations of fuzzy sets. However, in most cases, fuzzy set always requires predefined rules to make the final decision; and the rule generating procedure always requires expertise domain knowledge, which maybe labour intensive.

4.1.2 Soft Computing for Learning Path Design

In micro learning, a learning path is composed of a series of learning units, which connect with each other based on the mutual relationships, the requirements of the learning process, and the knowledge level of the target learner. In addition, each unit in the micro learning path is comparatively tinier than traditional online learning. Learning path design aims to provide a suitable learning sequence for an individual, which can enhance the learning engagement and optimize the learning outcomes. Unlike a conventional recommender system, which recommends discrete and unordered learning units, a learning path is a sequence of well-ordered learning units with specific condition of commencement and ending. Such sequences of learning resources or activities can be adopted as optimal paths for a certain user to achieve a certain learning goal.

Ant colony optimization (ACO) algorithm is used in many studies to tackle the path planning problem. In [39], an ACO model is proposed to detect learners' learning transition such as knowledge area, and learning goal. In this study, the authors suggested that similar learning paths could represent a certain learning goal and learning requirements of a certain group of learners, and a learning path finished by a large number of learners could be seen as a valid or optimal learning sequence. This unsupervised learning path recommending strategy is self-adjusting and does not require labelled data. However, ACO is very sensitive to the cold start problem as it requires predefined paths at the initial stage of the execution of algorithm. Interestingly, another study used improved ACO with adopted Mahalanobis distance to recommend learning paths to learners [40]. Such model can avoid the side effects of the high dimensional space problem.

4.1.3 Soft Computing for User Model Construction

A recommending process can be regarded as a process of filtering out irrelevant information based on the user's preference and requirements [41]. The key success of a recommender system depends on the effectiveness and efficiency of the filtering process [42, 43]. For a conventional recommender system, such effectiveness of the filtering results highly relies on similarity measures to determine proximity between two items or users [44]. As indicated in [45], the feat of a collaborative filtering system is highly dependent upon the effectiveness of the algorithm in finding the neighbourhood, which is most similar to the target user. A user model is the set of information that describes a user's profile and his/her historical records. The user model used in the recommender system highly influence the effectiveness of the recommending results.

As another branch of soft computing, genetic algorithm (GA) has been widely used as an adaptive weighting method in the recommender system [42, 43, 46], which can further optimize the user model and boost the performance of CF-based RS. Unlike conventional optimization method, such as gradient descent, in GA, the searching for the optimal solution is mainly based on three genetic operators, namely selection, crossover, and mutation. The highlight of GA parameter tuning process is the operation of mutation and crossover, which can 'break the box' and find the new combinations of factors not being captured and recorded in the training dataset. With such ability, GA can explore new feature combinations in the global area with a relatively small sample set, it also alleviates the requirement of large amount data in the training step. As an example shown in Figure 3, when using GA to explore feature combination, some rare combinations of features could be explored as well, even if they would not appear in the training set.
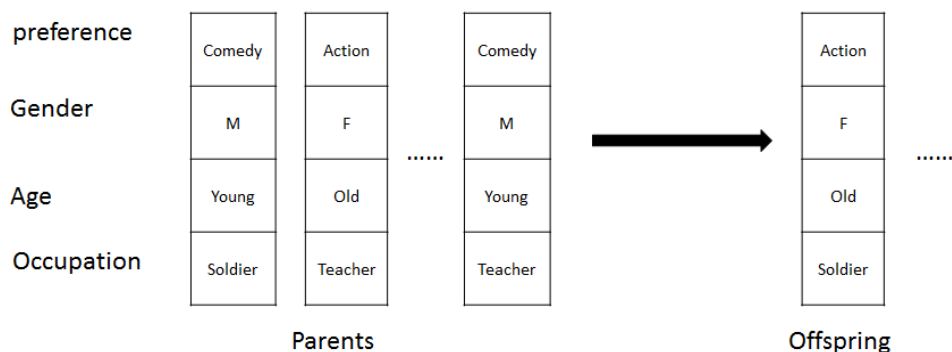

Figure 3. Genetic Algorithm for Exploring New Feature Combinations

Different to the ant colony optimization, which is mainly used for solving route optimization like learning path design, particle swarm optimization (PSO) is mainly used for tuning parameters [41, 47]. The principle of PSO is to mimic the movement of an organism population, such as birds and bees; each individual has a trend moving to close to the 'optimal' point/area in their living environment based on the historical movement information of the whole population and itself. Similar to the GA as discussed above, PSO can improve the collaborative-filtering recommending result by well tuning the weights of the involved user model [41, 47]. Comparing to GA, PSO requires less computational time while demonstrating higher accuracy [41, 47].

4.2 Transfer Learning

Transfer learning, which aims to utilize the knowledge gained from a particular domain and then apply it to a different domain, is now particularly popular in deep learning. The gained knowledge could be a trained model, or data set, or features. From the point of view of the research in micro learning, because there are very few sufficient and complete public data sets, many studies [20, 35, 48] are based on the gained knowledge from other domain. Using transfer learning methods to transfer sufficient labelled data from other domain(s) to the target domain is an indirect method to construct models and produce more labelled data. Such transferring strategy can alleviate the conflict between the data volume requirement, versus data dimension, and insufficient data in hand. Based on 'what to transfer', the approaches of transfer learning can be categorized into four types [49]:

1. Instance-transfer: re-weight some labeled data in the source domain for using in the target domain.
2. Feature-representation-transfer: find a 'good' feature representation that reduces the difference between the source and the target domain, and the error of classification and regression models.
3. Parameter-transfer: discover shared parameters or priors between the source domain and the target domain models, which can benefit from transfer learning [50, 51].
4. Relational-knowledge transfer: build a mapping function of relational knowledge between the source domain and target domains, where both domains are relational domains, and identical-independent distribution assumption is relaxed in each domain [52, 53].

Many prior studies [51, 53-55] pointed out that the CF-based recommender system suffered from the problem of data sparsity, especially for a newly launched system. The sparsity level of some data set could be higher than 90% [56]. Besides further mining the hidden information, predicting missing or blank rating information by using relevant data set from other domains was investigated by many researchers [50-53]. Most of the transformations are reached by utilizing the matrix factorization (MF) to learn the latent shared knowledge across different information sources.

User's binary preference data is used as the auxiliary information to predict the missing rating of the user-item rating matrix [50]. In [50], authors found that in many situations compared to numerical rating, binary rating such as like/dislike could easily let users express their feeling for certain items. The transformation was based on the assumption that both target and auxiliary data had identical user-specific and item-specific latent feature vectors. Similarly, users' information and items' information from an auxiliary domain were transformed to the target domain for filling the missing user-item rating value in another work [51]. However, the limitation for these two studies is also similar, as in many real-world scenarios we actually lack prior-knowledge and cannot guarantee that two different domain share similar users and items.

Some advanced progresses were achieved in [52, 53], where the proposed models integrated information from multiple different auxiliary domains for filling the missing rating in the target domain. The idea behind these two models was based on the fact that, items from different Websites shared similar latent patterns like genre and style, and users having similar preference or requirements could be grouped into the same cluster, which had reflected similar social aspects [53]. For micro learning, different online learning platforms might have similar targeted users and similar categories of learning materials. In these two studies, cluster-level rating matrices were generated to model the shared knowledge across different information sources.

4.3 Reinforcement Learning

Reinforcement learning (RL) has been widely used in various domains for sequential decision-making. The idea behind RL is to make sequential decisions (and take continuous actions) in an environment to maximize the notion of the cumulative reward. As mentioned in the previous section, learning path design is the extension of a

recommender system in micro learning. With the concept of RL, a learning path can be naturally seen as a sequence of individual learning activities, and the knowledge gained from the learning activities can be seen as the accumulated rewards from the learning activities.

RL is utilised for choosing the difficulty level of learning materials for learners in [57]. In this study, the proposed recommending strategy was based on the Zone of Proximal Development (ZPD) theory. ZPD [58] was used to define and quantify the 'area' most suitable for a learner based on cognitive and affective perspectives. In ZPD, a learner would be kept in his/her leading edge which fell in between 'confused' and 'bored' status; this area challenged but would not overwhelm the learner [58]. [57] also borrowed the solution of the Cliff-Walking problem [59]. The goal of the Cliff-Walking problem is to find an optimal route, which can arrive at goal state 'G' from the starting stage 'P' or any other positions without stepping into the 'cliff' area. As an example demonstrated in Figure 4, there are two routes start from state 'P' and arrive at 'G'.

During the learning activities, the negative feelings like being confused, bored, and frustrated are the 'cliffs' for which a learner should avoid. Two boundaries are used to separate the ZPD area from negative feelings (cliffs) namely confused and bored, then RL is used to optimize the learning path inside the ZPD area [57]; which is shown in Figure 5. Based on this approach, many extensions (even emotional information [60]) can be further applied to this original model. For micro learning, some other features such as distraction, time limitation, and learning speed can be involved to model the boundaries of best learning zones for individuals. Attached quizzes in micro learning at the end or middle of each micro learning unit can be used for calculating the accumulated reward for directing the RL training. SVM for multi-class classification can be used to define these boundaries in the high dimensional spaces. The primary challenge in applying this idea is to design the mathematical method to quantify, scale, and model the variables as well as the boundaries.

Figure 4. The Cliff-walking Problem

Figure 5. ZPD and Learning Path Optimization [57]

4.4 Context-Aware Recommendation

In a board sense, contextual factors can be time, location, the purpose, social relationship, and any other environmental information included in a learning activity. For micro learning, contextual information is the

representation of a set of factors which further depict the details of a specific learning scenario. [61] pointed out that for different 'contexts' that a user was involved in, the preference for items could be different. For example, a user's preference of the type of learning material might vary significantly with the change of location or device context; he/she might prefer reading when using a small screen mobile phone and prefer watching videos when sitting in front of a computer. As indicated in one survey article [62], even though some of the contextual information is still hard to capture and most existing systems barely use a fraction of it, being context-aware shows growing trend in the research of the recommender system.

Location is the most representative contextual information, which has great potential to further mine users' preference and intentions. Geo-location of a learner can reveal some latent information of a user's current learning environment, such as the surrounding noise levels [62]. For example, the noise level of a library and a shopping centre are considerably different. Furthermore, the noise level is a significant criteria to estimate a possible level of concentration or distraction of a learner at a specific time point [63].

A user's social network or the relationships among the whole group of users is another vital contextual factor, which greatly influences the user's preference. As argued in [64], people tend to associate with the ones who share a similar preference, and people who are close to each other often influence each other. This is also confirmed by the study [65], that the contextual information about users' relationships such as the social network can be used to exploit vital information and improve the quality of recommending results. For educational activities, classmates, best friends, or colleagues, might have similar learning requirements or similar learning interests; the relationship among users could be consequently useful for realizing the personalized learning service. Up to now, many studies [66-70] have tried to incorporate social information in the recommendation process. In [68], authors demonstrated a model combining the social network and other contextual information and proved its results as quite satisfactory. In their study, the random forest was used to partition the original user-item ranting matrix based on the contextual information. Similarly, in [69], a regularization term was used, which took into account the similarities between a user and his/her friends based on social information.

5 Current Challenges and Research Gaps

Except for several significant domain characteristics that were discussed at the beginning of Section 4, according to the reviewed studies, there are three other challenges and research gaps for the research of micro learning:

1. The difficulty of directly and effectively interpreting the content from multimedia learning resources;
2. The trade-off between the degree of personalization and system workload; and
3. The data challenges in the research of the entire micro learning process.

5.1 Content Analytics in Micro Learning

As discussed in Section 3, a great portion of segmentation and annotation strategies are based on the content of the learning resources. However, there is a huge research gap in interpreting and analysing the video or audio content, especially for the micro learning materials. As emphasised in Section 3, nowadays most of the studies heavily rely on OCR, ASR, NLP techniques, which are indirect approaches to interpreting and analysing the content of the learning resources. The combination of OCR, ASR, and NLP aims to transfer all audio and visual information into the textual form. Due to the technical difficulties in directly interpreting the content of the video stream or audio signal, textual information becomes the only remaining metadata that researchers can interpret and analyse. As discussed in [31], although automatically-generated metadata and annotations by using ASR or OCR are sometimes error-prone, they are practically two of the limited options for researchers to make the audio-visual content retrievable and accessible.

5.2 Trade-off between Personalization and System Workload

When a real-life problem involves user interactions, machine learning techniques are frequently used to construct the user modelling to represent the user's profile and other related information that matters in different complex scenarios. Such a model is intended to represent general user information. Conventionally, for the

instances of a user model, all users could have different feature values but share the same set of feature weightings. For a personalized online learning service, how nicely the user information can be modelled and represented determines the extent of personalization service can a system offer. Recently, many studies argue that, to boost the personalization of an RS in the educational scenario, it is necessary to construct a user model for each user individually [41-43, 45-47]. As discussed in [42], the main features reflecting different users' preference are naturally different; for example, some users mainly rely on their explicit ratings, some rely on the similar age and gender groups, whereas some others rely on all features. According to the relevant experiments carried out in the study [42], many cases indicate that, for different users the feature weights vary greatly, and sometimes for a specific user, some features do not contribute at all during the recommendation process.

Optimizing the features' weight individually for each user outperforms optimizing the features' weight for all users together. However, tuning features' weight for each user individually is very computationally time-consuming [42]. In other words, this weighting strategy pursues personalization of the system by constructing a user model for each user; it discards the generalization of conventional user model and sacrifices the computational efficiency of the system. Also, such weighting strategy might be very time sensitive. For an active user, some information about his/her profile might change very frequently when an interaction occurred with events such as rating new items or making new comments. This situation implies that, for active users, the user model needs to be updated frequently in order to maintain the recommendation accuracy. For the future research of micro learning, especially for the fast growing underlying data, it is necessary to carefully balance the trade-off between the degree of recommender's personalized service and the workload of computation behind the system.

5.3 The Challenges Related to the Available Datasets

According to discussions in the previous Sections, in a micro learning system, for carrying out different tasks, different processing modules require different types of data. Hence, the collection of the dataset for the research of computational intelligence in education should be task driven. For example, recommendation strategies heavily rely on the users' historical learning activities, while the annotation models will be mostly based on the content information of the learning resources. The readiness of the data is vital for the development of micro learning research. Due to the problematic availability of the public datasets, many research groups have involved the dataset with various flaws in their experiments. From the reviewed studies, insufficiency [32], inappropriateness [35] and the non-publicity [26] are the main data related problems impeding the development of current and future micro learning research. As most models are data-driven, sometimes, data refining is also a significant stage for ensuring the effectiveness of applying various machine learning approaches. Dirty data, such as unbalanced data, noise data, should be carefully pre-processed before pouring into the models.

Moreover, the datasets used in most researches so far only contained partial information, which separated the research of the complete micro learning process into several different subtopics. For instance, the dataset used for segmentation and annotation in the study [16] could not be applied to the following recommendation investigation, as it did not contain any user information. In most cases, it is impractical to directly fuse different datasets used in different studies, as they were captured from different sources and did not share the same set of users or learning resources. For the research of micro learning, the datasets used in many prior TEL studies have revealed fairly low reusability. To further promote the research of micro learning, researchers demand a more complete, sufficient, and reusable dataset, which can be used for the whole workflow modelling and validation.

6 Conclusion

In this paper, we discussed the significance of micro leaning as an emerging learning style, which is the consequence of the development of the Web based learning and education, and also the promotion and popularity of researches in the Big Data and machine learning areas. Such learning style has potential to fully and effectively utilize the fragmented time of people's daily lives.

We have also proposed a micro learning framework, which consists of two significant processing stages for realizing the personalized online learning service: learning materials preparation and learning material recommendation. The first stage is vital for generating micro learning materials, and the second stage is the

important in satisfying the personalized learning requirements. According to the studies that we surveyed in this paper, the technologies involved in different stages of the micro learning service have obvious overlaps. Machine learning, data mining and statistical analysis are critical and key technologies in constructing a delicate micro learning system which could be used under the context of the massive user and the massive learning resource. Especially, for interpreting the user's profile and the content information of learning resource, NLP, OCR, and ASR are three main useful tools for current and future research in this field.

Moreover, most of the reviewed literature focused on describing the educational problem from one single or few perspectives, which were still far from fully depicting the educational problem in the real-life scenario. To design a delicate micro learning service, researchers should continue paying more attention to investigate how to mine different aspects of information from the learning activities. Lastly, as most of the decision models are data-driven, researchers and communities should also take efforts to construct more sophisticated public datasets and make them available for shared research.

Our contributions in this paper are hopefully supporting the future research by providing the review of a primary framework an intelligent micro learning from a higher perspective. We also expect to inspire more potential solutions to the problems that researchers might face in the generic research area of e-learning or micro learning.

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