Unsupervised Learning Style Classification for Learning Path Generation in Online Education Platforms

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ABSTRACT

Online education, which educates students that cannot be present at school, has become an important supplement to traditional education. Without the direct supervision and instruction of teachers, online education is always concerned with potential distractions and misunderstandings. Learning Style Classification (LSC) is proposed to analyze the learning behavior patterns of online learning users, based on which personalized learning paths are generated to help them learn and maintain their interests.

Existing LSC studies rely on expert-labored labeling, which is infeasible in large-scale applications, so we resort to unsupervised classification techniques. However, current unsupervised classification methods are not applicable due to two important challenges: ***C1)*** the unawareness of the LSC problem formulation and pedagogy domain knowledge; ***C2)*** the absence of any supervision signals. In this paper, we give a formal definition of the unsupervised LSC problem and summarize the domain knowledge into problem-solving heuristics (which addresses ***C1***). A rule-based approach is first designed to provide a tentative solution in a principled manner (which addresses ***C2***). On top of that, a novel Deep Unsupervised Classifier with domain Knowledge (DUCK) is proposed to convert the discovered conclusions and domain knowledge into learnable model components (which addresses both ***C1*** and ***C2***), which significantly improves the effectiveness, efficiency, and robustness. Extensive offline experiments on both public and industrial datasets demonstrate the superiority of our proposed methods. Moreover, the proposed methods are now deployed in the Huawei Education Center, and the ongoing A/B testing results verify the effectiveness of the methods.

KEYWORDS

learning style classification, unsupervised classification, educational data mining, deep clustering, user behavior analysis

ACM Reference Format:
Zhicheng He[1*], Wei Xia[1*], Kai Dong[2], Huifeng Guo[1✉], Ruiming Tang[1✉], Dingyin Xia[2], Rui Zhang[3]. 2018. Unsupervised Learning Style Classification for Learning Path Generation in Online Education Platforms . In *Woodstock '18: ACM Symposium on Neural Gaze Detection, June 03–05, 2018, Woodstock, NY*. ACM, New York, NY, USA, 10 pages. https://doi.org/10.1145/1122445.1122456

1 INTRODUCTION

In the ongoing COVID-19 pandemic, many schools are closed worldwide [27]. Online education (a.k.a. online learning, e-learning, etc.) has since been adopted by more governments and schools to maintain the teaching schedule. Huawei Education, which aims to unlock education everywhere for everyone, has been providing online education solutions for years[1]. Supported by advanced communication technologies, remote students are taught in real-time through online courses, collaborative classroom, and intelligent after-school guidance, etc. Along with the achieved progresses, however, new problems also emerge. Compared with traditional face-to-face instructions, interaction patterns between teacher and students are completely changed as illustrated in Figure 1. Online users (a.k.a. students or learners[2]) interact with teachers in an indirect manner through the online system, leading to potential inadequate instructions, distractions, or even dropouts [20]. To help users understand the courses and engage them in learning, it is necessary to explore and exploit their learning behavior patterns.

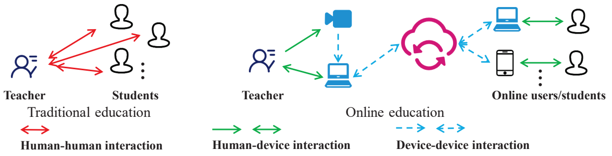

Figure 1: Illustration of traditional and online education.

Learning style modeling is such a pedagogy research that focuses on revealing users' learning behavior patterns [7, 11, 23]. As shown in Table 1, the famous and widely applied Felder-Silverman Learning Style Model (FSLSM) [11] depicts users' learning behaviors according to how they perceive, sense, process, and understand new knowledge. Take information sensory as an example, users with the visual learning style prefer to learn from visual materials like pictures and videos, while verbal users prefer texts and audio. The teaching quality can be greatly improved if users' learning styles can be correctly classified and properly utilized. Thus Learning Style Classification (LSC) is an important task for both traditional and online education.

Traditional pedagogy LSC studies are based on surveys, case studies, and expert analysis [7, 14, 19]. Apart from that, researchers also resort to machine learning techniques to solve the LSC task.

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[1] https://e.huawei.com/en/solutions/industries/education
[2] To avoid misunderstandings, we only use the word "user" in the rest of this paper.

Woodstock '18, June 03–05, 2018, Woodstock, NY

ACM ISBN 978-1-4503-XXXX-X/18/06…$15.00
https://doi.org/10.1145/1122445.1122456

Table 1: The Felder-Silverman learning style model [11].

Dimension	Label	Learning preferences
Perception	Sensory	sights, sounds, sensations
	Intuitive	possibilities, insights, hunches
Sensory	Visual	pictures, diagrams, graphs
	Verbal	words, sounds
Processing	Active	through activities or discussions
	Reflective	through introspection
Understanding	Sequential	in continual steps
	Global	in large jumps, holistically

Due to the need for expert knowledge, existing machine learning based approaches are built on carefully labeled but small datasets [1, 10, 30, 31], which lead to inefficiency and ineffectiveness in large-scale applications. Further, questionnaire-based user labeling is infeasible in online education platforms due to poor user experience. Without enough supervision, classifiers fail to learn the correct mapping from user features to learning style labels, which is a severe and challenging problem in LSC research. In this paper, we resort to unsupervised classification techniques.

Unsupervised classification is a classic research issue that assigns samples to one of the inherent categories without using labeled training samples [3, 22, 26]. Existing research works can be roughly divided into two major groups: i) pre-training methods that apply classifiers pre-trained on other datasets; ii) rule-based methods derived from expert-made rules. However, both kinds of approaches are inapplicable because LSC differs from other unsupervised classification problems with two challenges. First, LSC is less understood in the machine learning community, and the solutions should accord with existing pedagogy domain knowledge (***C1***). Second, no external labels are available to supervise the classifier training in terms of neither pre-training nor transfer learning (***C2***).

To solve the above challenges, we build from scratch two principled LSC solutions. Through extensive pedagogy literature survey and data analyses, we give a formal definition of the unsupervised LSC problem in machine learning language and summarize the expert knowledge into problem-solving heuristics (for ***C1***). A rule-based algorithm is first designed to explore the use of pedagogy domain knowledge and provide a naive solution (for ***C2***). However, the rule-based algorithm is vulnerable to data noises. When online changes happen, laborious trial-and-error analyses is needed to adjust the settings. To overcome these obstacles, a new Deep Unsupervised Classifier with domain Knowledge (DUCK) is proposed to further improve model effectiveness, robustness, and efficiency. The DUCK model consists of a deep clustering backbone model to learn representations and conduct clustering in a self-supervised manner, based on which expert-made rules are used to classify data (for ***C2***). To better integrate the domain knowledge, a behavioral preference constraint is put forward to extract user behavior patterns, and a smoothing component is also designed to understand the intrinsically skewed label distributions (for ***C1***). As a result, DUCK model not only improves the performances significantly, but also has great efficiency and robustness. In summary, the contributions of this paper are as follows:

- To our best knowledge, we are the first to give a formal definition of the unsupervised LSC problem in machine learning language. We elaborate the properties of the unsupervised LSC problem in terms of both literature and data analysis, based on which some useful domain knowledge is summarized.
- Under the guidance of the summarized domain knowledge, both a naive rule-based algorithm and a novel model named DUCK are proposed to solve the unsupervised LSC problem. Our DUCK model not only overcomes the absence of labeled data, but also integrates the domain knowledge well.
- Experiments on both public and industrial datasets validate the superiority of the proposed methods. Moreover, our methods are now deployed in the Huawei Education Center, and the online A/B testing results further show the important value of this work.

2 RELATED WORKS

2.1 Learning Style Classification

Learning style models refer to a series of pedagogy researches that reveal how people learn and prefer to learn [11, 15]. Many different learning styles have been proposed to discover learning preferences from different perspectives such as the FSLSM [11], the Kolb's learning styles [19], and the VARK model [23]. Researchers also focus on the learning style classification (LSC) task [1, 10, 31] where the proposed approaches can be divided into traditional and machine learning based categories.

Traditional pedagogy LSC research is based on surveys, case studies, and expert analysis [7, 12, 14, 19]. For example, the Solomon questionnaire [25] is adopted in [8] to analyze learning styles and improve multimedia teaching. While Prithishkumar and Michael use the VARK questionnaire to classify the sensory modality preferences in learning. Due to the reliance on expert analysis, traditional approaches are troubled by the low efficiency thus not applicable to online environments.

Machine learning techniques have also been adopted to pedagogy researches. He et al. apply topic model to assess the curriculum design [18] He et al. propose to use linear regression models to detect users' dropout risks [17]. When it comes to LSC research, Aissaoui et al. propose a fuzzy c-means algorithm to classify students under the FSLSM [1]. Dutsinma and Temdee classify students under the VARK model with decision trees [10]. However, due to the high prices in acquiring ground-truth labels, existing models are all built on small datasets [30], which leaves two major concerns: i) the low extensibility, and ii) the risk of losing effectiveness in face of large datasets. In face of million-scale users, traditional human-labored labeling becomes infeasible. So we propose an unsupervised LSC approach that solves the reliance on data labeling.

2.2 Unsupervised Classification

Unsupervised classification refers to a series of research works that classify samples without using labeled training data [3, 6, 22, 26]. Due to the various difficulties in data labeling, unsupervised classification has a wide range of applications including sentiment classification [6, 26], image classification [16, 22], and remote sensing [21]. To overcome the lack of supervision signals, pre-training [4], clustering [16, 29], and rule-based [6, 21, 26] approaches have all been explored to make the best use of data semantics and domain knowledge. As no pre-training datasets are available, this paper utilizes both clustering and expert-made rules.

3 PRELIMINARY

For the ease of elaboration, in this section, we first address some fundamental concepts including the notations, the adopted label system, and the problem definition. After that, we summarize the pedagogy background knowledge into problem-solving heuristics.

3.1 The FSLSM

The most vital issue of learning style research is the choice of learning style labels as many label systems have been proposed. This paper adopts the Felder-Silverman Learning Style Model (FSLSM) [11] which has found the most widespread applications and best fits the online education scenarios. As shown in Table 1, FSLSM classifies users from four orthogonal dimensions each of which has two opposite labels. Each user can be tagged with four FSLSM labels describing her/his learning styles from different perspectives. Two labels from different dimensions are orthogonal to each other, thus the LSC task can be split into four independent tasks. In this paper, we only consider the *Sensory* dimension because of its importance in learning material usage. However, the proposed method can be easily extended to other dimensions. Moreover, we add a new label "Neutral" to describe those non-significant users who are neither "Visual" nor "Verbal", resulting into a label set $\mathcal{L} = \{0,\ 1,\ 2\}$ where 0, 1, and 2 represents "Visual", "Neutral", and "Verbal" respectively.

3.2 Problem Formulation

Before elaborating the technical details of proposed methods, the basic definitions need to be addressed

Definition 1: Learning Style Classification (LSC). Suppose there are $|\mathcal{U}|$ online learning users $\mathcal{U} = \{u_1, u_2, \ldots, u_{|\mathcal{U}|}\}$, each user leaves some learning behavior logs $\mathcal{B} = \{\mathbf{b}_1, \mathbf{b}_2, \ldots, \mathbf{b}_{|\mathcal{U}|}\}$, LSC aims to assign a learning style label $l_i \in \mathcal{L}$ to each user u_i according to her/his learning behavior log $\mathbf{b}_i$.

In machine learning terminologies, LSC maximizes the posterior probability of u_i's learning style label l_i given the behavior log $\mathbf{b}_i$

$$l_i = \arg\max P(l_i|u_i, \mathbf{b}_i; \Theta), \quad \forall\, u_i \in \mathcal{U}, \tag{1}$$

where Θ is the model parameter set and $P(\cdot|\cdot;\Theta)$ is the probability function which can be implemented as a rule-based algorithm, a Bayesian model, or a deep neural network. Due to the absence of labeled data for the LSC task, we resort to the unsupervised classification approaches.

Definition 2: Unsupervised LSC. Given a set of unlabeled users $\mathcal{U}$ and the learning style label set $\mathcal{L}$, an unsupervised LSC algorithm classifies all users into $|\mathcal{L}|$ classes each of which indicates a unique learning style label in $\mathcal{L}$.

3.3 Pedagogy Domain Knowledge

As a classic pedagogy research topic, abundant theories and findings [1, 5, 7, 14] about the LSC task have been proposed and provide valuable insights. Here we summarize the most important findings into two heuristics that guide our problem-solving.

Heuristic 1: User Behavioral Preference. On the whole, visual users prefer to interact more with visual learning materials but less with verbal materials, and vice versa for verbal users.

In traditional pedagogy studies, expert-made questionnaires (e.g., the Solomon questionnaire [25]) are adopted to collect users' behavioral preferences on learning materials, which is inefficient in large-scale online applications. What is more, both the learning materials and interaction forms are getting richer and more diverse in the many online education platforms. So there needs an automatic method to extract user behavioral preferences without human laboring. In this paper, for a better exploration and utilization of user behavioral preferences, we propose to integrate such heuristic into an unsupervised classifier in a learnable way. Specifically, anchor features are first selected by experts to quantitatively measure the behavioral preferences in each class. And a constraint component is further proposed to promote the classification results to fit the desired class-wise behavioral preferences.

Heuristic 2: Label Distribution Skewness. In an unbiased sampling of users, the learning style label distribution is always skewed to the visual label.

As revealed in many pedagogy studies [12], there are always more visual users than verbal users. In some cases, researchers may even classify all users as visual [28]. However, it is an ineffective result to judge most users as visual due to the loss of distinctiveness. A reasonable classification result should make a trade-off between the inherent label distribution skewness and the usability of classification results. To achieve that, this paper proposes a new label distribution loss to tune the label distribution, thus liberates us from the tedious trial-and-error tests.

3.4 The Proposed Solutions

Inspired by the summarized heuristics, this work proposes both an intuitive rule-based algorithm and a deep unsupervised classifier for the LSC task, as illustrated in Figure 2. The rule-based algorithm is enlighten by both ***Heuristic 1*** and the unsupervised sentiment classification algorithms [6, 26] that decide the semantic orientation of a text according to the sentiment words in it. As shown in the gray block of Figure 2, anchor features are first extracted from the behavior logs, which serve similarly with the sentiment words. After that, anchor features are manually labeled as visual or verbal, and rules are made to calculate users' statistical significance on them. Then users are classified by the overall significance on all anchor features. Finally, evaluation and parameter tuning are conducted for further improvements. To further improve robustness and effectiveness, a novel Deep Unsupervised Classifier with domain Knowledge (DUCK) is proposed, as in the golden block of Figure 2. A DEC backbone model (blue block) [29] is devised to learn data representations and soft clustering in a self-supervised manner. On top of that, a behavioral preference loss and a label smoothing loss are proposed to integrate ***Heuristic 1*** and ***Heuristic 2*** respectively into model learning. For the ease of understanding, in the rest of this paper, we first present the rule-based algorithm to help clarify the problem-solving workflow, followed by the description of the deep model.

4 RULE-BASED APPROACH

Due to the absence of labeled samples, conventional supervised learning solutions are infeasible, so a rule-based algorithm is first

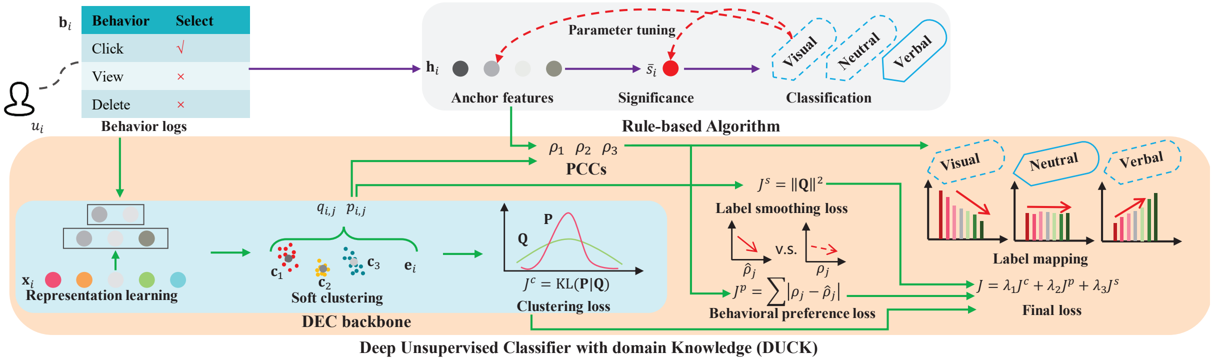


Figure 2: Framework of the proposed LSC solutions.

proposed to explore the utilization of domain knowledge. The rule-based algorithm is inspired by the unsupervised sentiment classification algorithms [6, 26] that classify texts with positive words (e.g., "wonderful" and "beautiful") as positive, while classify those with negative words (e.g., "awful" and "disgusting") as negative. Similarly, we propose to classify users' learning styles by rules on annotated behavior features, i.e., the anchor features.

4.1 Anchor Features

Anchor features are behavior features that can obviously describe users' learning styles, based on which classification rules can be made. To extract anchor features, in this paper, we focus on the proactive behaviors which provide the best evidences for revealing their true intents. For example, if a user always proactively clicks or zooms in pictures but seldom clicks texts, she/he is likely to be a visual user. On the other side, if a user passively sees some picture within a text, it contributes little to the probability of being visual. After a lot of analysis (details can be referred to in section 6.2), all K representative proactive user behaviors are chosen as anchor features such as zoom in a picture or reply a comment

$$\mathcal{A} = [a_1, a_2, \dots, a_K]. \tag{2}$$

The anchor features are sorted in a visual to verbal order. For example, a_1 might be zoom in a picture, and a_k might be click a comment. Thus for any $k < k'$, a_k is manually judged as more visual than $a_{k'}$. Then the numerical anchor feature values are calculated for each user u_i

$$\mathbf{h}_i = [x_{i,a_1}, x_{i,a_2}, \dots, x_{i,a_K}], \tag{3}$$

where x_{i,a_k} denotes the k-th anchor feature value. For example, x_{i,a_1} may calculate the frequency of zooming in pictures, while x_{i,a_K} is the normalized count of comments u_i has clicked.

4.2 Feature Significance

After obtaining $\mathbf{h}_i$ for each user, significance scores are further calculated to eliminate the biases brought by anchor feature value distributions. A user's significance score on the k-th anchor feature is decided by two threshold values $\omega_{k,0}$ and $\omega_{k,1}$ as

$$s_{i,k} = \begin{cases} 1 & h_{i,k} > \omega_{k,1} \\ -1 & h_{i,k} < \omega_{k,0} \\ 0 & \omega_{k,0} \le h_{i,k} \le \omega_{k,1} \end{cases}. \tag{4}$$

If $h_{i,k} > \omega_{k,1}$, the positive significance score $s_{i,k} = 1$ is assigned. And if $h_{i,k} < \omega_{k,0}$, the negative significance score $s_{i,k} = -1$ is assigned. Otherwise it is decided as non-significant with $s_{i,k} = 0$. It is non-trivial to manually set all $2K$ threshold values because different features have different distributions. In consideration of both the distinctiveness and fairness between anchor features, we use two percentile points $\mu_0, \mu_1 \in \{1, 2, \dots, 99\}$ to calculate the threshold values for each anchor feature a_k:

$$\begin{aligned} \omega_{k,0} &= \text{Percentile}(\{h_{1,k}, h_{2,k}, \dots, h_{|\mathcal{U}|,k}\}, \mu_0), \\ \omega_{k,1} &= \text{Percentile}(\{h_{1,k}, h_{2,k}, \dots, h_{|\mathcal{U}|,k}\}, \mu_1), \end{aligned} \tag{5}$$

where Percentile$(\cdot,\cdot)$ calculates the percentile value according to the given percentile points.

4.3 Classification Rules

Intuitively, if a user is always positively significant on visual anchor features but negatively significant on verbal ones, she/he is probably a visual user. Following that, users are classified by the average significance score on all anchor features

$$\bar{s}_i = \frac{1}{K}\sum_{k=1}^{K} s_{i,k} \times \text{Type}(a_k), \tag{6}$$

where the switch function Type$(\cdot)$ returns 1 for visual a_ks but -1 for verbal a_ks. Regulated by the switch function, a visual user always obtains a high and positive $\bar{s}_i$ value, while a verbal user gets a low and negative $\bar{s}_i$. So two thresholds $-1.0 < \tau_0 < \tau_1 < 1.0$ are adopted to decide the learning style labels by distinguishing the $\bar{s}_i$ values,

$$l_i = \begin{cases} 0 & \bar{s}_i > \tau_1 \\ 1 & \tau_0 \le \bar{s}_i \le \tau_1 \\ 2 & \bar{s}_i < \tau_0 \end{cases}. \tag{7}$$

4.4 Parameter Tuning

There are four hyper parameters in the rule-based algorithm, i.e., the percentile points (μ_0 and μ_1) and the significance threshold values (τ_0 and τ_1). Following the conventional practice, trial-and-error tests are adopted to search for the best parameter settings. However, such a tuning process is not only laborious and time-consuming, but also vulnerable to data noises and online changes. For example, when the APP's GUI is updated or some new function is added, distributions of anchor features will be influenced. Consequently, the previous parameter setting turns ineffective and tuning is needed again. To further improve robustness and effectiveness, a deep model is proposed in the next section.

5 DEEP UNSUPERVISED CLASSIFICATION

The rule-based algorithm has three main drawbacks: i) the poor robustness; ii) the underuse of rich user features; and iii) the neglect of ***Heuristic 2***. To overcome these drawbacks, a novel Deep Unsupervised Classifier with domain Knowledge (DUCK) is proposed.

5.1 Backbone Model Architecture

All main-stream deep classifiers consist of two vital building components, i.e., representation learning and supervised label prediction. The representation learning component is responsible for feature semantic extraction and exploitation, while the supervised label prediction component interprets the supervision signals for parameter optimization. However, the absence of labels makes the supervised prediction infeasible. So the proposed DUCK model takes a clustering module to learn representations and mapping rules for label prediction. The clustering module should meet two conditions: i) it can be optimized with gradient techniques; ii) it is applicable to large-scale datasets. In this paper, we choose the classic Deep Embedded Clustering (DEC) model [29] (blue block in Figure 2) and leave other clustering algorithms to future works.

5.1.1 ***Representation Learning.*** To represent a user $u_i \in \mathcal{U}$, a feature vector $\mathbf{x}_i \in \mathbb{R}^{d^x}$ is extracted from the behavior log $\mathbf{b}_i$

$$\mathbf{x}_i = \text{Extract}(\mathbf{b}_i), \tag{8}$$

where Extract$(\cdot)$ covers all offline feature pre-processing steps including feature selection, smoothing, and z-score normalization. To incorporate useful information as much as possible, more features are extracted into $\mathbf{x}_i$ than the K anchor features.

To facilitate subsequent learning processes, a multi-layer perceptron (MLP) component is applied to learn user representation $\mathbf{e}_i \in \mathbb{R}^{d^e}$ from the raw $\mathbf{x}_i$,

$$\mathbf{e}_i = \text{MLP}(\mathbf{x}_i), \tag{9}$$

where MLP$(\cdot)$ is made up with stacked dense layers with the ReLU activation function and dropout. Following the original work [29], MLP$(\cdot)$ is initialized with a stacked denoising autoencoder.

5.1.2 ***Soft Clustering.*** With the learned representations, users are first clustered, based on which they are further classified with rules. The soft probability of user u_i belonging to the j-th cluster is estimated according to the t-distribution similarity between $\mathbf{e}_i$ and the cluster centroid $\mathbf{c}_j \in \mathbb{R}^{d^e}$,

$$q_{ij} = \frac{(1 + \|\mathbf{e}_i - \mathbf{c}_j\|^2)^{-1}}{\sum_{j'=1}^{|\mathcal{L}|}(1 + \|\mathbf{e}_i - \mathbf{c}_{j'}\|^2)^{-1}}, \tag{10}$$

where $\|\cdot\|^2$ is the l_2 norm. The $\mathbf{c}_j$s are first initialized by clustering the initialized user representations, then optimized during training. Clustering algorithms like KMeans [2] or Gaussian Mixture Model (GMM) [24] can be adopted as analyzed later in experiments.

5.1.3 ***Clustering Loss.*** For parameter optimization and clustering refinement purposes, DEC designs a self-supervised clustering loss function. The intuition is that high-confidence clustering assignments (i.e., big q_{ij}s) should be encouraged, while low-confidence clustering assignments (i.e., small q_{ij}s) should be punished. So the target clustering probabilities are designed to sharpen the distribution of q_{ij}s:

$$p_{ij} = \frac{q_{ij}^2/f_j}{\sum_{j'}^{|\mathcal{L}|} q_{ij'}^2/f_{j'}}, \tag{11}$$

where $f_j = \sum_{i'}^{|\mathcal{U}|} q_{i'j}$ is the soft clustering frequency. As illustrated in Figure 2, high-confidence q_{ij}s get even higher p_{ij}s, while small q_{ij}s get almost zero p_{ij}s. By minimizing the KL divergence between q_{ij}s and p_{ij}s, clear margins between different q_{ij}s are gradually achieved for each user u_i,

$$J^c = \text{KL}(\mathbf{P}|\mathbf{Q}) = \sum_{i=1}^{|\mathcal{U}|}\sum_{j=1}^{|\mathcal{L}|} p_{ij}\log\frac{p_{ij}}{q_{ij}}, \tag{12}$$

thus the clustering results are more convincible. The final cluster label c_i of u_i is estimated by finding the nearest centroid in the embedding space as

$$c_i = \arg\min_j \|\mathbf{e}_i - \mathbf{c}_j\|^2 = \arg\max_j q_{ij}, \tag{13}$$

where $j \in \{1, 2, \ldots, |\mathcal{L}|\}$. Equation (13) can be used to infer the clustering of testing users. For classification, the number of clusters is fixed as the number of learning style labels, i.e., $|\mathcal{L}| = 3$.

5.1.4 ***Label Mapping Rules.*** After the deep model training and cluster label inference, each user is assigned into one of the clusters $C_1, \ldots, C_{|\mathcal{L}|}$. However, the class labels are still unclear because the clustering is obtained from inherent user behavioral similarities rather than supervised learning. Inspired by ***Heuristic 1***, the learning style label of each cluster is first decided by the overall behavioral preferences of the contained users. So the same class label can then be assigned to all users within it.

The anchor features are used to decide the learning style label of each cluster. For all users in the j-th cluster C_j, the average anchor feature vector is first calculated,

$$\overline{\mathbf{h}}_j = \text{Avg}(\{\mathbf{h}_i \mid u_i \in C_j\}), \tag{14}$$

where Avg$(\cdot)$ calculates the element-wise average value of a set of vectors. Further, a histogram is drawn to show the K average anchor feature values in a visual to verbal order. Due to the behavioral preferences in ***Heuristic 1***, histogram of the visual cluster will have a descending trend, while a ascending trend can be observed for the verbal cluster, as illustrated in Figure 3. To obtain a quantitative measurement, the Pearson Correlation Coefficient (PCC) between $\overline{\mathbf{h}}_j$ and the anchor feature index $\mathbf{k} = [1, \ldots, K]$ is calculated,

$$\rho_j = \text{PCC}(\overline{\mathbf{h}}_j, \mathbf{k}), \tag{15}$$

where PCC$(\cdot,\cdot)$ calculates the PCC between two vectors. If $\rho_j \to -1$, a descending trend can be observed in the histogram, which indicates the visual class as in Figure 3. Otherwise $\rho_j \to 0$ and $\rho_j \to +1$ imply the neutral and verbal classes respectively. According to the above analysis, we rank all $|\mathcal{L}| = 3$ ρ_js, where the minimal, median, and maximal values correspond to the visual, neutral, and verbal classes respectively.

5.2 Behavioral Preference Constraint

The pedagogy domain knowledge is obviously underused in the backbone model, because ***Heuristic 1*** is only used in the post-training label mapping and ***Heuristic 2*** is not even considered.

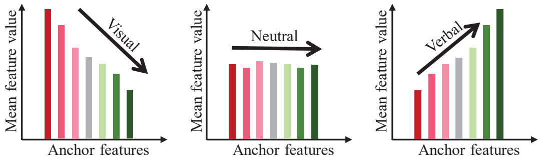


Figure 3: Examples of the mean anchor feature histograms.

Thus the classification results are likely to deviate from the pedagogy assumptions. To better solve the LSC problem, we attempt to integrate the two heuristics into model learning with two new components as in Figure 2.

5.2.1 *Early Label Assignment*.

Both the rule-based approach and the backbone model consider ***Heuristic 1*** at the post-training stage. To make the best use of domain knowledge, we propose to consider it during model learning. However, the behavioral preference is loosely defined at the class-level rather than a strict constraint applied to individual users. Because the desired behavioral preferences differ between any two learning styles, applying ***Heuristic 1*** in the learning process means that the class labels should be known during training, which is inconsistent with the backbone. To solve that, we improve the backbone with an early label assignment right after the initialization of clustering centroids.

After the clustering initialization, the PCCs (ρ_j^0s) are calculated for each of the $|\mathcal{L}|$ clusters as in Equation (15). With the same rules described in section 5.1.4, the j-th cluster can be assigned with a class label l_{C_j} which will be fixed in subsequent model training. On the one hand, with the indicated behavioral preference information, each l_{C_j} will enhance the representation learning of users in C_j. On the other hand, the improved user representations will in turn promote the clustering to better fit the early assigned labels.

5.2.2 *Behavioral Preference Assessment in Training*.

Since C_j is assigned a class label l_{C_j} right from the beginning, the desired class-wise behavioral preference trend is definite, thus the behavioral preference constraint can be applied. Within each training step, the soft clustering probabilities q_{ij}s are used to decide the current cluster labels of all users as in Equation (13). Therefore, the behavioral preference of users in the j-th cluster C_j can be assessed with the PCC ρ_j of the mean anchor feature vector $\overline{\mathbf{h}}_j$ as in Equation (15).

5.2.3 *Behavioral Preference Loss*.

Based on the early assigned class label l_{C_j} of each cluster, the target feature distribution PCC $\hat{\rho}_{C_j}$ can be induced as in section 5.1.4, i.e., -1, 0, and 1 for the visual, neutral, and verbal clusters respectively. Then the behavioral preference loss is proposed to minimize the difference between the current ρ_j and the target $\hat{\rho}_{C_j}$,

$$J^p = \frac{1}{|\mathcal{L}|}\sum_{j=1}^{|\mathcal{L}|} |\rho_j - \hat{\rho}_{C_j}|. \tag{16}$$

Through optimizing J^p, the behavioral feature distribution of each cluster is driven to gradually fit ***Heuristic 1***.

5.3 Label Distribution Smoothing

Apart from the behavioral preferences, the label distribution skewness in ***Heuristic 2*** is also an important issue. On the one hand, equal-sized classification results do not fit the pedagogy domain knowledge. On the other hand, extremely skewed label distribution makes the classification results indistinguishable and unusable. To make a trade-off, the l_2 loss of the soft clustering matrix $\mathbf{Q}$ is adopted to smooth the clustering probabilities

$$J^s = \frac{1}{|\mathcal{B}|}\|\mathbf{Q}\|^2 = \frac{1}{|\mathcal{B}|}\sum_{i=1}^{|\mathcal{U}|}\sum_{j=1}^{|\mathcal{L}|} q_{ij}^2. \tag{17}$$

With J^s, DUCK can find a balancing point between the label distribution skewness and the usability of classification results.

5.4 Model Optimization

Finally, the newly proposed behavioral preference loss and the label smoothing loss are combined together with the clustering loss,

$$J = \lambda_1 J^c + \lambda_2 J^p + \lambda_3 J^s, \tag{18}$$

where λ_1, λ_2, and λ_3 are hyper-parameters to weigh different losses. For model optimization purpose, the Adam optimizer is adopted.

6 EXPERIMENTS

6.1 Datasets

To evaluate the effectiveness of the proposed approaches, we conduct experiments on both public and industrial datasets.

MOOC Dataset. The MOOC dataset is a publicly available dataset for online education research [13]. Many user behavior logs have been tracked and recorded. In the two-year learning activity logs, about 180 million behavior events are recorded. After deleting the inactive or abnormal users, about 460 thousand users are extracted for experiments, based on which 22 user behavioral features and 9 anchor features are extracted.

Industrial Dataset. The Industrial dataset is collected from the Huawei Education Center. User behavior events are tracked by the APP and reported to the backstage servers. Logs within one month are taken for experiments where approximately 1 million anonymous users are sampled, and about 38 million behavior events are extracted. After some data analysis and processing, 15 behavior features are selected and 7 of them are used as anchor features.

6.2 Anchor Feature Selection

The anchor features are used to decide the learning style label of each cluster and to construct the behavioral preference constraint, we show how the anchor features are extracted here. Following ***Heuristic 1***, the more active an individual user interact with visual learning materials, the more likely her/his learning style is visual, and vise versa. So we focus on users' frequent proactive behaviors conducted on representative learning materials. Table 2 shows some representative proactive behaviors such as play a video and create a comment, while the full list is not provided due to space limitation. After that, the occur rate of each proactive behavior is calculated by the normalized occurrence count, and the indicative degree is manually judged accordingly. Finally, the strongly indicative behaviors are selected as anchor features. Examples of the MOOC dataset are in Table 2, where three anchor features are selected.

Table 2: Examples of the anchor feature selection process.

Behavioral object		Behavior	Style	Occur	Indicate
Visual	courseware,	play	Visual	1.0	Strong
	video,	click	Visual	0.4626	Strong
	figure, etc.	close	Verbal	0.2253	Weak
Verbal	text about,	click	Verbal	1.0	Strong
	comment,	create/save	Verbal	0.0910	Weak
	audio, etc.	close/delete	Verbal	0.0005	Weak

6.3 Evaluation Metrics

Due to the absence of groundtruth labels, three unsupervised metrics are adopted for offline evaluations, i.e., BPL, NES, and DBI. To further verify the effectiveness of proposed methods, online A/B testing is also conducted and evaluated by the dropout rate and learning efficiency, which will be described later in Section 7.

- **BPL**. BPL is short for Behavior Preference Loss which is used to assess the understanding of the user behavioral preferences as in Equation (16). It is calculated on the final classification results and lower values mean better performances.
- **NES**. NES is short for Normalized Entropy Score which is adopted to evaluate the category imbalances:

$$\mathrm{NES} = -\frac{1}{\log_2 |\mathcal{L}|} \sum_{j=1}^{|\mathcal{L}|} \frac{|C_j|}{|\mathcal{U}|} \log_2 \frac{|C_j|}{|\mathcal{U}|}. \tag{19}$$

  A lower NES value means a more skewed learning style label distribution. But extremely low NES values (i.e., NES = 0) are undesirable as the classification results will be unusable.
- **DBI**. DBI is short for the Davies-Bouldin Index [9]. It assesses the data separation state between clusters. A lower DBI indicates better separated classes. We further divide DBI with the user number to reduce the value range.

6.4 Compared Methods

Both classic clustering algorithms and deep models are adopted for comparision. As the baselines provide only clustering results, we improve them with the same label mapping rules in section 5.1.4.

- **KMeans**. The classic KMeans [2] algorithm that iteratively updates the sample clustering and centroids.
- **Gaussian Mixture Model (GMM)**. GMM [24] clusters data by discovering the Gaussian distributions.
- **BIRCH**. BIRCH [32] first inserts samples into a feature tree as the leave nodes, then merges them for clustering.
- **DEC-KM**. The standard DEC model with the KMeans centroid initialization, which is our backbone model.
- **DEC-GMM**. The KMeans initialization of DEC is replaced with GMM for comparision.
- **Rule-based approach**. The proposed rule-based approach is described as in Section 4.
- **DUCK-KM**. Our proposed DUCK model with the KMeans initialization as described in Section 5.
- **DUCK-GMM**. A variant of our DUCK model where the KMeans initialization is replaced with GMM.

Detailed experimental settings are provided in Appendix A.

6.5 Overall Performance Evaluation

Table 3 exhibits the experimental performances of compared methods. From the presented results, several observations can be found.

- First, the lowest BPL scores are always achieved by our proposed methods (DUCK-KM < DUCK-GMM < Rule-based < others), which demonstrates the effectiveness of our methods in discovering and utilizing the user behavioral preferences (***Heuristic 1***). Because the pedagogy domain knowledge is neglected, both traditional (KMeans, GMM, and BIRCH) and deep (DEC-KM and DEC-GMM) baselines fail to understand the behavioral preferences and obtain high BPL scores.
- Secondly, both traditional (KMeans, GMM, and BIRCH) and deep (DEC-KM and DEC-GMM) fail to discover the distribution skewness (***Heuristic 2***) with high NES values. The rule-based approach successfully reveals the skewness on the MOOC dataset (NES=0.6136 for training and NES=0.6126 for testing) but fails on the sparse Industrial dataset (NES=0.8391 for training and NES=0.8931 for testing). However, DUCK-KM successfully understands ***Heuristic 2*** and achieves significantly lower NES values on both datasets. Due to different data densities, DUCK-GMM achieves the lowest NES values on the MOOC dataset but fails on the Industrial dataset.
- Thirdly, KMeans always achieves the lowest DBI scores, while the rule-based approach consistently achieves the highest DBI scores. In contrary, the DUCKs successfully balance the understanding of domain knowledge and better clustering separation, where DUCK-GMM achieves the second best DBI scores on both datasets.

Taken overall, we claim that our DUCK models perform best.

6.6 Ablation Study

The proposed DUCK model improves the DEC backbone with the behavioral preference constraint and the label distribution smoothing. To evaluate the effectiveness of the proposed components, the ablation study is conducted by removing each component and results into three sub-models, i.e., DUCK/BPC (the behavioral preference constraint is removed), DUCK/LDS (the labels distribution smoothing is removed), and DUCK/BPC/LDS (the original DEC backbone without either component). Experimental results are presented in Table 4. Due to the lack of space, only the BPL and NES scores on the MOOC dataset are reported, and the KMeans centroid initialization is adopted. As can be observed, the removal of either component leads to significant performance drops, which demonstrates the necessity and effectiveness of the proposed components. Furthermore, DUCK/LDS performs better than DUCK/BPC in NES on both training and testing sets. The reason is that the behavioral preference constraint plays the key role in understanding and utilizing domain knowledge, based on which the label distribution smoothing component further tunes the classification results.

6.7 Behavioral Preference Analysis

Heuristic 1 provides the most important pedagogy domain knowledge in LSC tasks, i.e., the behavioral preference. To visualize how it is reflected in the classification results, histograms of the mean anchor feature values are drawn in Figure 4. Due to space limit, only

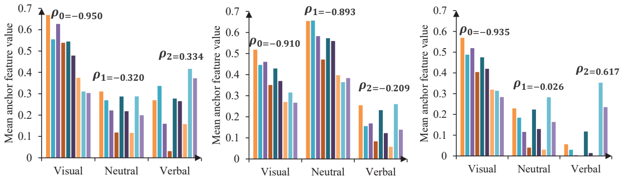
Table 3: The overall performance evaluations, all metrics are the lower the better. The best performances are boldfaced and the second best results are underlined.

Models	MOOC training			MOOC testing			Industrial training			Industrial testing		
	BPL	NES	DBI	BPL	NES	DBI	BPL	NES	DBI	BPL	NES	DBI
KMeans	0.7357	0.9093	**1.2724**	0.7340	0.9112	**1.2745**	0.5451	0.7380	0.9604	0.5400	0.7367	0.9622
GMM	0.6747	0.9952	1.4221	0.6768	0.9957	1.4241	0.5535	0.8717	1.3042	0.5540	0.8711	1.3068
BIRCH	0.6840	0.9592	1.4255	0.6820	0.9606	1.4344	0.3252	0.5850	1.3937	0.3244	0.5858	1.3948
DEC-KM	0.7323	0.9684	1.4420	0.7308	0.9703	1.4472	0.4584	0.7711	1.0583	0.4561	0.7690	1.0624
DEC-GMM	0.7341	0.9695	1.4331	0.7369	0.9715	1.4390	0.3152	0.8632	1.2077	0.3159	0.8621	1.2116
Rule-based	0.3440	0.6136	2.5943	0.3453	0.6126	2.5505	0.2639	0.8391	2.2883	0.2633	0.8931	2.2680
DUCK-KM	**0.1487**	0.6201	1.9514	**0.1472**	0.6204	1.9771	**0.2335**	**0.4123**	**0.9271**	**0.2330**	**0.4085**	**0.9192**
DUCK-GMM	0.2416	**0.4793**	1.2978	0.1810	**0.4786**	1.3551	0.2511	0.8854	1.2136	0.2537	0.8836	1.2181

Table 4: The ablation study results.

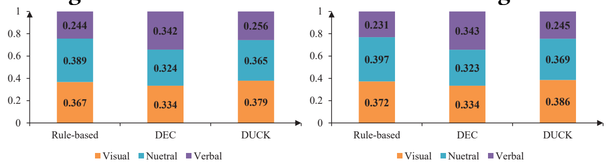
Models	Training		Testing	
	BPL	NES	BPL	NES
DUCK	**0.1487**	**0.6201**	**0.1472**	**0.6204**
DUCK/BPC	0.7281	0.9503	0.7259	0.9518
DUCK/LDS	0.3437	0.7767	0.3422	0.7778
DUCK/BPC/LDS	0.7323	0.9684	0.7308	0.9703

the histograms of the rule-based approach, DEC-KM, and DUCK-KM on the MOOC dataset are presented. It is hard to distinguish the neutral and verbal classes from the histograms of the rule-based approach, but the PCCs are distinguishable. Due to the neglect of domain knowledge, neither the histograms nor the PCCs of DEC are distinguishable. In contrast, both the histograms and the PCCs of DUCK successfully illustrate the different behavioral preferences, which proves the understanding of ***Heuristic 1*** by DUCK.



(a) Rule-based approach (b) DEC (c) DUCK

Figure 4: Mean anchor feature value histograms.



(a) Training (b) Testing

Figure 5: Visualization of label distribution skewness.

6.8 Label Distribution Skewness

The label distribution skewness in ***Heuristic 2*** is another concerning issue of LSC research. To analyze whether different algorithms can discover the skewness, the proportions of the number of users in different classes are calculated in the log-log scale, i.e., $\sigma_j = \frac{\log(|C_j|)}{\sum_{j'}\log(|C_{j'}|)}$. Due to space limit, only the results of the rule-based approach, DEC-KM, and DUCK-KM on the MOOC dataset are presented. As shown in Figure 5, DEC fails to discover the skewness where more users are distinguished as verbal. By comparison, both the rule-based approach and DUCK successfully reveal the skewness, and DUCK further wins by discovering more visual users. So we claim that the DUCK model well understands ***Heuristic 2***.

7 ONLINE DEPLOYMENT

As illustrated with ***the solid green blocks*** in Figure 6, the proposed LSC solutions have been deployed in the Huawei Education Center[3] which is a widely used auxiliary teaching system in China. Learning style labels guide the system to generate personalized learning paths that accord with users' learning preferences, thus reduces dropout and improves efficiency. In a recommended learning sequence, visual users get more visual learning materials (purple blocks) while verbal user get more text-like materials (gold blocks).

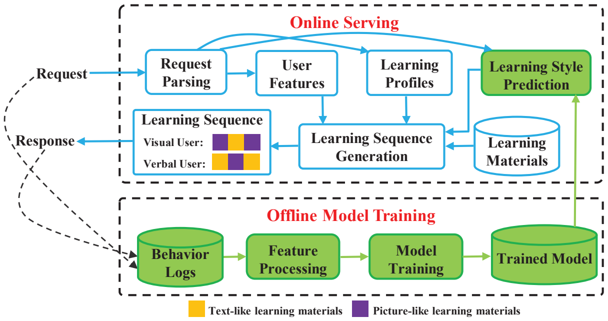


Figure 6: Online deployment of the proposed LSC approaches in the learning path generation system.

7.1 System Overview

In offline training, user behavior logs are used for feature processing and model training. The logs include user behavior events such as click, create, read, and write. We use Huawei's self-developed log collection system to store and collect users' online behavior data. Data processing and feature engineering are then conducted on the big data platforms. After that, the proposed models are trained with Intel Xeon 6278C CPUs (26 cores), Tesla V100*4 GPU, and 240GB Host memory. The trained models are then stored online and predict the learning style labels for users in real-time.

In online serving, when a user requests a learning sequence on the APP, an acquisition request is send to server. The request is first parsed to obtain user ID and other necessary information. Based on these data, the system further generates the real-time user features, retrieves the learning profiles (e.g., learning targets and learned courses), and predicts the learning style. By taking all these information into account, a personalized learning sequence is generated which is composed of various learning materials including micro-courses, articles, videos, audio, and pictures. The

[3] https://appgallery.huawei.com/app/C101178177

predicted learning style label has an important impact on the learning sequence generation process. Usually, a visual user's learning sequence contains more picture-like materials, while a verbal user obtains more text-like materials as illustrated in Figure 6.

7.2 Online A/B Testing

The online A/B testing is conducted and evaluated with two vital metrics, i.e., the dropout rate (DR) and the learning efficiency (LE). DR is defined as the ratio between lost users and active users

$$\mathrm{DR} = \mathrm{LU}(T_1)/\mathrm{AU}(T_2),$$

where $\mathrm{LU}(T_1)$ counts users who have left the APP for at least T_1 days and $\mathrm{AU}(T_2)$ counts all active users in the past T_2 days. LE is defined as the average learning time for a new knowledge point

$$\mathrm{LE} = \mathrm{LT}(T_2)/\mathrm{KP}(T_2),$$

where $\mathrm{LT}(T_2)$ summarizes the learning time and $\mathrm{KP}(T_2)$ summarizes the number of learned knowledge points of all users within T_2 days. We set T_1 and T_2 as 30 and 180 respectively.

Due to the long time it takes to make a full and prudent online evaluation, A/B testing of the rule-based approach starts from December 2021 and is still ongoing, while the DUCK model is still waiting for scheduling. The only difference between experimental and comparison groups is the use of learning style labels. So far, the rule-based approach ***achieves a 1.2% decrease on DR and a 3.5% increase on LE.*** Such significant improvements successfully verify the effectiveness of our work.

8 CONCLUSION AND FUTURE WORK

This paper focuses on solving the new and vital unsupervised learning style classification task in online education platforms. A rule-based approach is first provided as a naive solution, based on which a novel model named DUCK is further proposed. With a clustering objective, data representations are learned from the intrinsic feature semantics. After that, a behavioral preference constraint and a label distribution smoothing component are further devised to make better use of the pedagogy domain knowledge. Offline experimental results on both public and industrial datasets verify the effectiveness of proposed methods. Moreover, the online deployment and A/B testing results validate the value of this work. In future work, we will explore the use of self-supervised learning techniques on the LSC task.

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A EXPERIMENTAL SETTINGS

A.1 Implementation Details

The sklearn package is adopted to implement the KMeans, GMM, and BIRCH algorithms[4]. A public Tensorflow version of the standard DEC-KM [5] is used, based on which we further implement the DEC-GMM, DUCK-KM, and DUCK-GMM algorithms by ourselves. For all compared methods, both datasets are randomly split into training and testing sets with a 80 to 20 ratio. After all unsupervised algorithms are trained, the same label mapping rules are used to find the final class labels as described in section 5.1.4,

A.2 Hyperparameter Settings.

For all compared methods, the number of clusters or classes is set to 3. The same data pre-processing steps are shared across all methods including feature processing, anchor feature selection, and the split of training and testing sets. Other parameter settings are selected with grid search on each dataset as listed in Table 5.

Table 5: Detailed parameter settings for the two datasets.

Parameter	Value	
	MOOC	Industrial
Percentile point μ_0	50	50
Percentile point μ_1	75	75
Classification threshold τ_0	-0.5	-0.1
Classification threshold τ_1	0.1	0.2
KM initialize runs	20	5
KM maximum #iter	100	20
GMM covariance type	spherical	spherical
GMM initialize runs	5	2
GMM maximum iteration #iter	20	20
BIRCH merging threshold	0.05	0.05
BIRCH maximum sub-cluster #iter	30	30
DEC/DUCK-KM MLP size	[128]	[64, 256]
DEC/DUCK-GMM MLP size	[128]	[64, 256]
DEC/DUCK-KM initialize #iter	5000	250
DEC/DUCK-KM finetune #iter	10000	500
DEC/DUCK-GMM initialize #iter	500	800
DEC/DUCK-GMM finetune #iter	1000	1000
Loss weights, λ_1, λ_2, λ_3	1.0, 1.0, 1.0	1.0, 1.0, 1.0
Learning rate	0.00005	0.00005
Batch size	512	512

[4] https://scikit-learn.org/stable/modules/clustering.html

[5] https://github.com/HaebinShin/dec-tensorflow