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Automatic Determination of Learning Styles

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Abstract—Learning styles refer to various approaches of learning. Various theories regarding learning styles have been proposed and different models are available to determine learning style of an individual. However, after analyzing 176 students' questionnaires using Felder Silverman model we observed that learning styles boundaries are not crisp.

As opposed to existing automatic techniques, we propose to use non-crisp clustering algorithms to automatically de-termine overlapping studying patterns of students registered for Saint Mary's University's online Courses. We applied crisp as well as non-crisp (fuzzy and rough) clustering algorithms to categorize students as studious, crammers, workers according to their study patterns.

Keywords-Learning Styles; Overlapping learning styles; Felder Silverman model; Non-crisp clustering; Rough K-means; FCM

1. INTRODUCTION

Learning styles refer to the approaches or ways of learning that helps an individual to learn best. The idea of individualized "learning styles" involves educating meth-ods, particular to an individual. This concept has gained popularity in recent years and several researchers try to extract a learner model based on the personality factors like learning style, knowledge factors like user's prior knowledge, and behavioral factors like user's browsing history.

Different behavioral features can be extracted and ana-lyzed from the learning behavior of a student to identify learning styles. Several models for defining and measuring learning styles have been proposed, such as Kolb [7] proposed that learners can be classified into convergent learners, divergent learners, assimilators, and accommoda-tors. Felder and Silverman's model [2] proposed learn-ing styles based on the categories like intuitive/sensitive, global/sequential, visual/verbal, inductive/deductive and active/reflective. The Keefe's [6] learning style test iden- tifies learner's Sequential Processing Skill, Discrimination Skill, Analytic Skill and Spatial Skill. Fleming's VARK model [3], Stangl's model [9] are among the several other models proposed for determining learning styles.

There are attempts to infer students' learning styles automatically from their content access behavior in an online course. Chang et al. [1] proposed a learning style classification mechanism to classify and then identify stu-dents' learning styles. They collected learning behavioural features of elementary school students and then classified these behavioral features using improved K-nearest neigh-bor (K-NN) classification, which is combined with genetic algorithms (GA).

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Ozpolat et al. [8] too extracted the learners' model by classifying the learners using NBTree classification algorithm in conjunction with Binary Relevance classifier. They compared these results with the learning style results obtained using traditional questionnaire method.

These above mentioned automatic techniques do not identify overlapping learning styles. Hence, we propose non-crisp clustering to identity students that show charac-teristics of different learning styles. over a span of certain time period.

The remaining paper is organized as follows. In section2, we discuss our observations of overlapping learning styles for students. Section 3 describes about clustering techniques and Fuzzy C-means algorithm, and Rough K-means algorithm in particular. Section 4 elaborates about the data set used for experiment purpose. We discuss and analyze the experimental results in the fifth section followed by conclusions.

2. OVERLAPPING LEARNING STYLES

In this section we share our observation regarding over-lapping learning styles. We used Felder Silverman model to understand Learning Styles of 176 students of MCA and MCM courses at the IMCC institute, Pune. Table I displays the spread of students in various categories.

We can see in our own data, the number of students demonstrating characteristics of both active and reflec-tive learning styles are 72.67%; 59.66 % of students showed characteristics of both Sensing and Intuitive learn-ing styles. For Visual/Verbal learning styles combination 52.55% sudents reflect characteristics of both the styles.

Input:

k : the number of clusters,

D(n, d): a data set containing n objects where each object has d dimensions,

m: a fuzzification parameter (> 1),

iter: maximum allowed number of iterations

δ : a termination criterion

Output:

A set of clusters. A fuzzy coefficients matrix U that represents objects' degree of membership for each cluster.

Steps:

arbitrarily initialize $U = [u_{ij}]$ as a $n \times k$ fuzzy membership coefficients matrix

repeat

At step *t* obtain the centroid vector $C^{[t]} = \vec{c_j}$ using $U^{(t)}$ as in Eq. 2

update the $U^{(t+1)}$ using $U^{(t)}$ as follows

$$u_{ij} = \frac{1}{\sum_{a=1}^{k} \frac{d(\vec{x_i} - \vec{c_j})}{d(\vec{x_i} - \vec{c_a})}^{\frac{2}{m-1}}}$$

until no change;

Figure 1.The Fuzzy C-means algorithm

Data of IMCC, India		Data of Graf et al.	
Learning Style	No. of Students (%)	Learning Style	No. of Students (%)
Active / Reflective	Active: 14.54 Reflective: 12.79 Moderate: 72.67	Active / Reflective	Active: 24 Reflective: 15 Moderate: 61
Sensing / Intuitive	Sensing: 37.33 Intuitive: 3.01 Moderate: 59.66	Sensing / Intuitive	Sensing: 29 Intuitive: 17 Moderate: 53
Visual / Verbal	Visual: 32.73 Verbal: 14.72 Moderate: 52.55	Visual / Verbal	Visual: 64 Verbal: 3 Moderate: 33
Sequential / Global	Sequential: 18.47 Global: 13.72 Moderate: 67.81	Sequential / Global	Sequential: 16 Global: 16 Moderate: 68

Table 1 PERCENTAGE NUMBER OF STUDENTS OF PARTICULAR LEARNING STYLES.

A total of 67.81 % of students showed characteristics of Global/Sequential learning styles.

Similar trend of overlapping learning styles can be seen in a work published by Graf et al. [5].

If the student shows balance between two complementing learning styles, Graf et al. refer such students as balanced students. For Active/Reflective, Sensitive/Intuitive, Visual/Verbal and Sequential/Global learning styles the percentage number of balanced students reported are 61%.53%, 33% and 68% respectivelly. Their data was obtained after analyzing 207 students filled questionnaires from Austria and Newzeland.

In both these examples we see handful number of students reflecting characteristics of multiple learning styles. These examples underline the concept of overlapping learning styles for students. These observations strong enough to motivate us to identify overlapping learning styles, using non-crisp clustering analysis. Details of noncrisp clustering algorithms are presented in next section.

3. NON-CRISP CLUSTERING

In addition to clearly identifiable groups of objects, it is possible that a data set may consist of several objects that lie on the fringes. The conventional clustering techniques mandate that such objects belong to precisely one cluster. Such a requirement is found to be too restrictive in many data mining applications [10]. In practice, an object may display characteristics of different clusters. In such cases, an object should belong to more than one cluster, and as a result, cluster boundaries necessarily overlap [11]. Fuzzy set representation of clusters, using algorithms such as fuzzy C-means, makes it possible for an object to belong to multiple clusters with a degree of membership between 0 and 1 [13]. Whereas, rough set based clustering provides a solution that is less restrictive than conventional clustering and less descriptive than fuzzy clustering.

Both the Fuzzy clustering and Rough clustering are described in the following subsections.

3.1. Fuzzy Clustering

Fig. 1 delineates the steps of Fuzzy C-means algorithm.

The Fuzzy C-means (FCM) allows objects to belong to two or more clusters with a degree of belonging to clusters, as in fuzzy logic. Developed by Dunn in 1973 [12] and improved by Bezdek in 1981, this method is based on minimization of the following objective function:

$$\sum_{i=1}^{n}\sum_{j=1}^{k} u_{ij}^{m}\ d(\vec{x_i},\vec{c_j}) \quad , \quad 1 < m < \infty \tag{1}$$

where n is the number of objects and each object is a d dimensional vector. A parameter m is any real number greater than 1, u_{ij} is the degree of membership of the i^{th} object $(\vec{x_i})$ in the cluster j, and $d(\vec{x_i},\vec{c_j})$ is the Euclidean distance between an object and a cluster center c_j.

In Fuzzy C-means, the centroid of a cluster is obtained by average of all objects, weighted by their degree of membership to a cluster:

$$\vec{c_j} = \frac{\sum_{i=1}^{n} u_{ij}^{m}\ \vec{x_i}}{\sum_{i=1}^{n} u_{ij}^{m}} \tag{2}$$

FCM is an iterative algorithm that terminates if

$$max\left(\left|u_{ij}^{t+1} - u_{ij}^{t}\right|\right) < \delta \tag{3}$$

where δ is a termination criterion between 0 and 1, and *t* is the iteration step.

3.2. Rough Clustering

The rough K-means approach for clustering is of interest to several researchers. Lingras and West[14] provided RKM algorithm based on an extension of the K-means algorithm[17], [16].

Incorporating rough sets into K-means clustering requires the inclusion of the concept of lower and upper bounds. The incorporation requires redefinition of the calculation of the centroids to include the effects of lower and upper bounds. The criteria to determine whether an object belongs to the lower and upper bounds of a cluster is also modified.

We represent each cluster $c_i, 1 \leq i \leq k$, using its lower $\underline{A}(c_i)$ and upper $\overline{A}(c_i)$ bounds. All objects that are clustered using the algorithm follow basic properties of rough set theory such as:

(P1) An object $\vec{x}$ can be part of a lower bound of at most one cluster

(P2) $\vec{x} \in \underline{A}(\vec{c}_i) \Longrightarrow \vec{x} \in \overline{A}(\vec{c}_i)$

(P3) An object $\vec{x}$ is not part of any lower bound

$$\Updownarrow$$

$\vec{x}$ belongs to upper bound of 2 or more clusters.

Fig. 2 depicts the general idea of the algorithm. An object is assigned to lower and/or upper bound of one or more clusters. For each object vector, $\vec{v}$, let $d(\vec{v}, \vec{c}_j)$ be the distance between itself and the centroid of cluster $\vec{c}$. Let $d(\vec{v}, \vec{c}_i) = \min_{1 \leq j \leq k} d(\vec{v}, \vec{c}_j)$. The ratios $d(\vec{v}, \vec{c}_i)/d(\vec{v}, \vec{c}_j)$,$1 \leq i, j \leq k$, are used to determine the membership of $\vec{v}$. Let $T = \{j : d(\vec{v}, \vec{c}_i)/d(\vec{v}, \vec{c}_j) \leq threshold \text{ and } i \neq j\}$.

1) If $T \neq \emptyset$, $\vec{v} \in A(\vec{c}_i)$ and $\vec{v} \in A(\vec{c}_j), \forall j \in T$. Furthermore, is not part of any . lower bound.The above criterion guarantees that property (P3) is satisfied.

2) Otherwise, if $T = \emptyset$, $\vec{v} \in \underline{A}(\vec{c}_i)$ In addition, by property (P2), $\vec{v} \in \overline{A}(\vec{c}_i)$.

The values of *p* (a threshold), *w lower, w upper* are finalized based on the experiments described in [11].

4. EXPERIMENT

In order to test whether the overlapping learning styles can be determined by an automated approach, we need sufficiently large number of web log data of students visit to certain online courses. The 176 students who filled the questionnaires have been registered and asked to access the online course material. Their accessing pattern is being tracked. But we have yet to get sufficient data to automatically determine and cross check their learning styles. Hence we decide to use another online course access log data to test how non-crisp clustering can be used to determine overlapping study pattern of these students.

The study data was obtained from web access logs of courses of Saint Mary's University. Web users were identified based on their IP address. This also made sure that the user privacy was protected. A visit from an IP address started when the first request was made from the IP address. The visit continued as long as the consecutive requests from the IP address had sufficiently small delay.

The web logs were preprocessed to create an appropriate representation of each user, corresponding to a visit. The abstract representation of a web user is a critical step that requires a good knowledge of the application domain. Based on studying patterns described below, we categorized these students in following three categories.

- **Studious:** These visitors download the current set of notes. Since they download a limited/current set of notes, they probably study class-notes on a regular basis.
- **Crammers:** These visitors download a large set of notes. This indicates that they have stayed away from the class-notes for a long period of time. They are planning for pretest cramming.
- **Workers:** These visitors are mostly working on class or lab assignments or accessing the discussion board.

Previous personal experience with the students in the course suggested that some of the students print preliminary notes before a class and an updated copy after the class. Some students view the notes on-line on a regular basis. Some students print all the notes around important days such as midterm and final examinations. In addition, there are many accesses on Tuesdays and Thursdays, when in-laboratory assignments are due. On and off-campus points of access can also provide some indication of a user's objectives for the visit. Based on some of these observations, it was decided to use the following attributes for representing each visitor [15]:

- On campus/Off campus access.
- Day time/Night time access: 8 a.m. to 8 p.m. were considered to be the daytime.
- Access during lab/class days or non-lab/class days: All the labs and classes were held on Tuesdays and Thursdays. The visitors on these days are more likely to be workers.
- Number of hits.
- Number of class-notes downloads.

The first three attributes had binary values of 0 or 1.The last two values were normalized. The distribution of the number of hits and the number of class-notes was analyzed for determining appropriate weight factors. Different weighting schemes were studied. The numbers of hits were set to be in the range of [0,5]. Since the classnotes were the focus of the clustering, the last variable was assigned higher importance, where the values fell in the range [0, 10].

Input:

k: the number of clusters,

D(n; d): a data set containing *n* objects where each object has *d* dimensions,

p: a threshold value (1.4),

w lower: relative importance assigned to a lower bound (0.75),

w upper: relative importance assigned to an upper bound (0.25),

: a termination criterion (0.00001),

iter: maximum allowed number of iterations.

Output:

A set of clusters. Each cluster is represented by objects in lower region and in boundary region (upper bound)

Steps:

arbitrarily choose *k* objects from *D* as the initial cluster centers (centroids);

repeat

(re)assign each object to lower/upper bounds of appropriate clusters by determining its distance from each

cluster centroid,

update the cluster means (centroids) using the number of objects assigned and relative importance

assigned to lower bound and upper bound of the cluster;

until no change;

Figure 2. The Rough K-means algorithm

Tabel 2 VISITS CORRESPONDING TO DIFFERENT LEARNING STYLE.

Cluster	FCM	RKM		K-means
		Lower	Boundary	
Studious	1429	1600	2761	1914
Crammers	543	831	824	526
Workers	2174	2565	2879	5525

The total number of visits are 7965. The RKM algorithm is implemented in Java whereas MATLAB softwares standard functions are used to get results for fuzzy clustering. For FCM the threshold for stopping the clustering process was set at 10^{-5} and m was equal to 2.

5. RESULTS AND DISCUSSION

Table II shows the cardinalities of conventional clusters, the rough K-means based clusters, and the sets with fuzzy memberships greater than 0.6. The actual numbers in each cluster vary based on the characteristics of the course. For example, in the clustering results, the course had significantly more workers than studious visitors as these visits corresponds to first term course. Whereas for second term course we observed a natural progression as the percentage of studious visitors increased. A detailed course wise result analysis of this data can be obtained at [4].

Here we are more interested to see whether any visits are grouped to multiple clusters or not. WE can see that all 7965 visits are categorized to three different clusters crisply by the conventional K-means clustering algorithm. Students manifested by a set of visits are grouped to any one of the categories. Whereas RKM categorizes students corresponding to 1600 visits in a lower region of 'Studious' cluster as 'Studious'. Moreover, RKM also conveys that other students corresponding to 2761 visits of a boundary region of the cluster demonstrate features of more than one cluster including that of 'Studious' cluster. The FCM also identify those students demonstrating multiple studying pattern over a period of time.

6. CONCLUSION

Automatic determination of learning styles by analyzing the behavioral patterns of students' access/visits to online course contents is a topic interest to many researchers.

We used Felder Silverman model to determine learning styles of students. We discussed the concept of overlapping cluster and showed how non-crisp clustering can be used to identify objects that demonstrate characteristics of multiple Learning styles.

All the 176 students have been asked to use 'Moodle' LMS and their access behavior is being tracked to obtain their learning styles automatically. We shall compare these results with manually obtained learning style results in future.

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