Classification of Online Course Teaching Cases Based on an Improved Clustering Method

https://doi.org/10.3991/ijet.v17i24.35945

Liyang Li(✉)
Department of Economics and Trade, Shijiazhuang University of Applied Technology, Shijiazhuang, China
2017010857@sjzpt.edu.cn

Abstract—The classification and sharing of online course teaching cases based on students' individual learning needs can help teachers save time and cost in preparation of lessons and enrich their teaching content, and what is more, it is in line with the digitalization trend of the modern data-driven education. Currently, there has been few research on the combination of new information technology with teaching case classification, and the research is not adequate on the existing algorithms for classification of online course teaching cases. Therefore, this paper takes the teaching cases of online open courses of finance as the object, and studies the classification method for online course teaching cases based on an improved clustering method. First, the text clustering problem of finance teaching cases was described, and the conversion process of the abstracts of the case text and the evaluation method for the importance of words to teaching cases were given. Then, the key sentences were extracted from the text of the finance teaching cases, and the related algorithm was introduced. After that, the clustering flow chart for long texts of finance teaching cases was shown, and the principle of the combined clustering algorithm for finance teaching cases with uneven distribution of long texts and short texts was described in detail. The experimental results verified the effectiveness of the proposed algorithm.

Keywords—cluster analysis, online course, teaching case, text classification

1 Introduction

With the update of technologies like cloud computing and artificial intelligence and the vigorous development of online open courses, teaching cases have become the core of online learning resources, and with the continuous updating of new platform learning resource combinations and configuration models, the classification and sharing of online course teaching cases are also developing [1–9]. The digital network environment where online open courses are taught and the wide application of student portrait analysis systems in distance education [10–14] are the foundation and support for the breakthroughs and innovations in the classification and sharing of online course teaching cases for students' individual learning needs. Through classification and sharing of online course teaching cases, teachers can save time and cost in preparation of lessons and enrich their teaching content. This is in line with the digitalization trend of the modern data-driven education [15–23].

Yang et al. [24] used the virtual ideal sequence construction for case text classification, and built a grey relational model based on information diffusion to avoid rank reversal when the decision-making information available is insufficient or the decision object changes. The results show that the grey relational model based on information diffusion and virtual ideal sequence can effectively avoid rank reversal. Liang et al. [25] takes the objective data at the Department of Computer Technology and Application, Qinghai University as an example, and proposed two effective classification methods: Convolutional Neural Network (CNN) and Stacked Bidirectional Long Short Term Memory (LSTM), and then conducted sentiment value calculation, descriptive analysis and feature analysis based on classification, and further dug the basic information contained in the text teaching evaluation. The experimental results showed that the average classification accuracy of this method could reach 98%, which effectively solved the problems of text classification and application in teaching evaluation. The method has been applied in the actual teaching improvement by the Department of Computer Technology and Application, Qinghai University, and its effectiveness further proved the advanced nature of the method. When English teaching text is regarded as an ontology, how to describe its attributes effectively is a problem. However, currently there is not enough research on the automatic extraction of English teaching text labels. Li [26] proposed that intelligent English teaching has become an inevitable trend in the development of English teaching models in the future, so it is necessary to apply the intelligent text recognition technology. Based on the support vector machine, this study used a convolutional neural network algorithm to effectively classify English teaching text.

Through review of the existing research results, it can be found that, thanks to the continuous exploration and practice of scholars at home and abroad, there have been many studies on the innovation and optimization of teaching case analysis, design, and database construction. However, few has been done on the combination of new information technology with teaching case classification, and the research is not adequate on the existing algorithms for classification of online course teaching cases. Therefore, this paper takes the teaching cases of online open courses of finance as the object, and studies the classification method for online course teaching cases based on an improved clustering method. Section 2 describes the text clustering problem of finance teaching cases, and gives the conversion process of the abstracts of the case text and the evaluation method for the importance of words to teaching cases. Section 3 completes the extraction of key sentences from the text of the finance teaching cases, and introduces the related algorithm. Section 4 gives the clustering flow chart for long texts of finance teaching cases, and describes in detail the combined clustering algorithm for finance teaching cases with uneven distribution of long texts and short texts. The experimental results verified the effectiveness of the proposed algorithm.

2 Description of the teaching case classification problem

There is massive amount of text information of finance-related teaching cases available on the existing online platforms. Such information is usually unlabeled, and the process of labeling it by category is the text clustering of finance teaching cases. For the clustering of long text of finance teaching cases, due to the large number of words contained in the text of each case, which makes it difficult to effectively extract features, a long text clustering algorithm was introduced for classification of finance teaching cases.

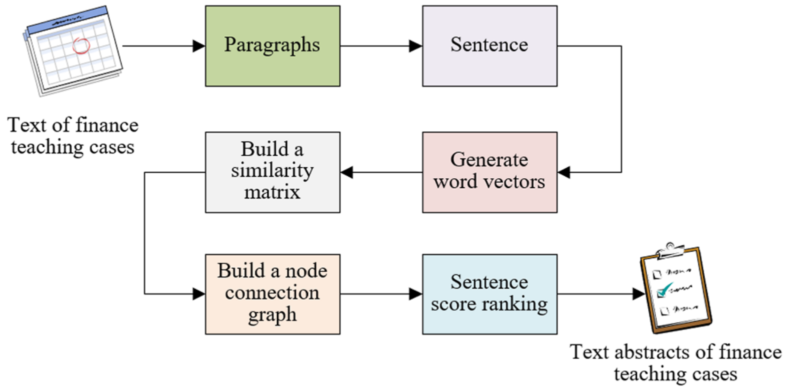

Fig. 1. Conversion process of teaching case text abstracts

With the development of online open courses and the continuous growth of digital online learning resources, the text data of finance teaching cases are booming. In order to achieve effective classification, it is necessary to convert the content of finance teaching cases into abstracts. Figure 1 shows the process of how to convert the text of teaching cases into abstracts.

The features of text are the key to distinguishing the text of finance teaching cases. At present, the commonly used feature extraction method is to perform word segmentation and word frequency statistics of the finance teaching case text. Before sentences were formed, this paper firstly conducted term frequency – inverse document frequency to achieve information retrieval and text mining of finance teaching case text, that is, to evaluate the importance of words to teaching cases. Assuming that the number of times a word appears in the finance teaching case document e_j is represented by $m_{i,j}$, the calculation formula of the word frequency is expressed as follows:

$$tf_{ij} = \frac{m_{i,j}}{\sum_{l} m_{l,j}} \tag{1}$$

The denominator of the above equation is the sum of the number of times each of the words has appeared in e_j. Suppose the total number of finance teaching case documents in the corpus is represented by $|E|$, and that the number of finance teaching case documents containing the word o_i by $|\{j:o_i \in e_j\}|$, then the formula for calculating the inverse document frequency is as follows:

$$idf_i = log \frac{|E|}{|\{j : o_i \in e_j\} + 1|} \tag{2}$$

If the word is not in the corpus, the denominator of the inverse document frequency calculation formula is 0, and $|\{ j{:}o_i \in e_j\}|+1$ can be used. The high-weight term frequency – inverse document frequency is generated based on two frequencies – high word frequency and low document frequency. The former is for finance teaching case documents, and the latter is for all teaching case documents containing the word. The calculation formula is expressed as follows:

$$TF - IDF = tf_{ij} * idf_i \tag{3}$$

3 Extraction of key sentences from the text of teaching cases

The curse of dimensionality and the similarity of words are the common problems in the extraction of text features of finance teaching cases. In order to solve these problems, this paper firstly constructed the corresponding word vectors for the finance teaching case text based on *Word*2*Vec*.

In order to make the constructed algorithm better understand the text language, this paper vectorized the natural language of the finance teaching case text, and adopted the continuous bag of words model with three layers – input layer, projection layer and output layer. Suppose there is finance teaching case text ($FTtext(q)$, q), where q is a word in the text, and $FTtext(q)$ consists of a total of $2d$ words before and after the word q.

Assuming that the length of the word vector is represented by n, the word vectors containing the $2d$ words in $FTtext(q)$ in the input layer of the continuous bag of words model satisfy $u(FTtext(q)_1)$, $u(FTtext(q)_2)$, ..., $u(FTtext(q)_{2d}) \in R^n$.

The projection layer of the continuous bag of words model stacks the $2d$ vectors, that is, $a_q = \Sigma^{2d}_{i=1} u(FTtext(q)_1) \in R^n$.

Output layer: the output layer corresponds to a binary tree where leaf nodes are words that have appeared in the corpus, and a weight is the number of times each word appears in the corpus.

For a set R containing N finance teaching case documents, where $R_i (i = 1, 2, \ldots, M)$, perform preprocessing of the finance teaching case text set R. If the text of the finance teaching cases is Chinese, use the word segmentation tool *Jieba* to complete word segmentation, and if it is written in English, use the tool *NLTK* to achieve word segmentation. After the word segmentation is completed, the finance teaching case text set is represented by R_{New}. By training of R_{New} through the continuous bag of words model, the N-dimensional word vector Q corresponding to each word in each finance teaching case document can be obtained, that is, $Q = (u_1, u_2, \ldots, u_N)$. After collection, a complete set of word vectors of the finance teaching case text can be obtained, which is represented by R_{TO}.

A piece of finance teaching case text R_1 containing O sentences can be equivalent to a graph with O nodes. Let the word vector of each word be represented by $Q = (u_1, u_2, \ldots, u_N)$, and the sentence RO by $RO = \{(Q_1, Q_2, \ldots, Q_m), m = L(RO)\}$. Suppose the finance teaching case text has two sentences RO_i and RO_j, where the sentence $RO_i = \{(Q^i_1, Q^i_2, \ldots, Q^i_m), m = L(RO_i)\}$, and $RO_j = \{(Q^j_1, Q^j_2, \ldots, Q^j_n), m = L(RO_j)\}$. The single sentence vector of RO_i is denoted by Q_m^i, and that of RO_j by Q_n^j, and the word similarity threshold by $\tilde{\omega}$. If the similarity between the word Q_m^i in the sentence RO_i and the word Q_n^j in RO_j is greater than $\tilde{\omega}$, then introduce Q_m^i and Q_m^j into the intersection set $\Phi(RO_i, RO_j)$, and there is:

$$\Phi(RO_i, RO_j) = \{Q_m^i, Q_n^j \mid Q_m^i \in RO_i \,\&\, Q_n^j \in RO_j \,\&\, sim(Q_m^i, Q_n^j) > \tilde{\omega}\} \tag{4}$$

Suppose the length of the sentence set in RO_i is denoted by m, and that the length of the sentence set in RO_j by n. In this paper, the intersection of RO_i and RO_j is divided by $(m + n)$ to calculate the sentence similarity of the finance teaching case text. The formula is as follows:

$$SIM(RO_i, RO_j) = \frac{\Phi(RO_i, RO_j)}{(m+n)} \tag{5}$$

It is assumed that the set of nodes linked with RO_i is denoted by $PN(RO_i)$, that the set of nodes linked with RO_j by $PN(RO_j)$, that the similarity between RO_i and RO_j by $SIM(RO_i, RO_j)$, and that the damping factor by e. The score calculation formula of node RO_i is expressed as follows:

$$QR(RO_i) = (1-e) + e * \sum_{RO_j \in PN(RO_i)} \frac{SIM(RO_i, RO_j)}{\sum_{RO_l \in PN(RO_j)} SIM(RO_j, RO_l)} QR(RO_j) \tag{6}$$

After several iterations of the nodes, the QR value will tend to be stable. Sort all QR values from high to low to obtain the candidate ranking CR. Nodes corresponding to high QR values are more important, while those corresponding to low QR values are less important.

The length of the finance teaching case document CR in the candidate ranking is represented by O, the extraction ratio σ, and the threshold of the sentence length HJ. If the number of sentences in the finance teaching case document is small, O is smaller than HJ, and the original financial teaching case document is retained. Otherwise, the original teaching case document is segmented. The following formula expresses the key sentence KRO in the finance teaching case document:

$$KRO_{\text{new}} = \begin{cases} CR[:O*\varepsilon] & if\,(O > HJ) \\ CR & if\,(O \le HJ) \end{cases} \tag{7}$$

The new finance teaching case document composed of key sentences is represented by KRO_{new}, and the segmentation ratio s. The larger the value of s is, the closer KRO_{new} is to CR; and the smaller the value of s is, the greater the difference is between KRO_{new} and CR.

4 Clustering analysis of teaching case text

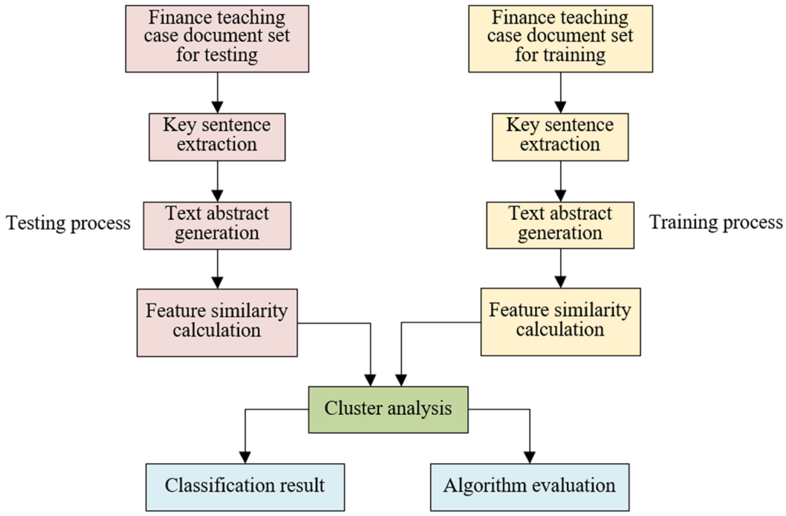

Fig. 2. Clustering flow chart of long text of finance teaching case documents

Some finance teaching case documents have long text. Figure 2 shows the clustering flow chart of long finance teaching case text. The algorithm firstly mines the text of the original finance teaching case based on *Word2ve* to obtain the finance teaching case text set *KRO* with key features, and then randomly assigns *KRO* to *L* clusters. Let the cluster label of each finance teaching case document be denoted as *D*, the number of teaching case documents in category *D* as n_D, the number of words in category *D* as m_D, and the number of times the word *Q* appears in category *D* as m_D^Q.

Set the number of iterations *X*. After each iteration, calculate the probability that each teaching case document *e* falls within each category based on the Dirichlet mixed polynomial model, and reassign the finance teaching case document *e* to the category with the highest probability. At the same time, update and save the information including *D*, n_D, m_D and m_D^Q. After the iteration is over, eliminate the categories with 0 finance teaching case document, and retain the categories with non-zero documents.

For the finance teaching case text set with uneven distribution of long text and short text, in order to improve the accuracy of the clustering algorithm, this paper further optimized the *K-means* clustering algorithm which is of good accuracy and high computational efficiency. The optimized algorithm can calculate the similarity between finance teaching case text based on the relationship between the entities in finance teaching case text and their information, which effectively improves the clustering effect of finance teaching case text.

In the *K-means* algorithm, suppose that the number of clusters of finance teaching case documents is *D*, that the *i*-th cluster e_i, and that its center n_i, and that the set of clusters $E = \{e_i\}(i = 1, \ldots, D)$, then there is:

$$n_i = \frac{1}{|e_i|} \sum_{a_j \in e_i} a_j \tag{8}$$

The purpose of clustering finance teaching case text is to minimize the sum of the distances between the center n_i of each cluster and all nodes in the cluster. The following formula defines the sum of distances:

$$SK(e_i) = \sum_{a_j \in e_i} DIS(a_j, e_i) \tag{9}$$

For clustering of finance teaching case text, the distance of nodes is characterized in this paper based on the cosine similarity *CosS*.

$$DIS(a_j, e_i) = 1 - CosS(a_j, e_i) \tag{10}$$

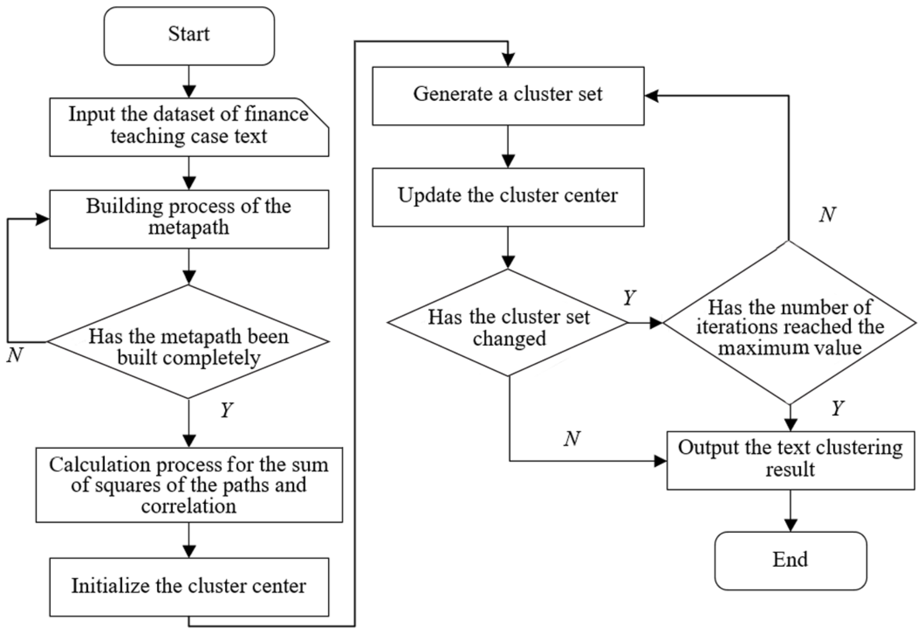

Fig. 3. Flow chart of the combined clustering algorithm

As there is a huge volume of finance teaching case text, it is a question as how to cluster similar text to achieve further acquisition of effective case text information. If the source, title, and keywords of the finance teaching case text are the same but the meanings are different, this will affect the quality of text clustering. This paper combined the meta-path with the *K-means* algorithm. Figure 3 shows the flow chart of the combined clustering algorithm. The following section takes a one-way meta-path of "keyword-text source" for illustration, where the path is represented by *XU*.

Assuming there are M keywords, and that the corresponding keyword set is represented by $X = \{x_1, x_2, \ldots, x_M\}$, that the number of paths *XU* is represented by N, and that the value of each path corresponding to each keyword is represented by $PA\_XU =$

$\{xu_1{:}V_1, xu_2{:}V_2, \ldots, xu_M{:}V_M\}$, then the sum of squares of the path corresponding to each keyword can be calculated by the following formula:

$$x_l^2 = \sum_{n=1}^{N} (PA\_XU \cdot x_l u_n)^2 (l \in [1, M]) \tag{11}$$

Based on all the calculation results calculated by the above formula, the sum of the squares of the paths corresponding to all keywords can be further obtained, which is expressed as $X^2 = \{x_1^2, x_2^2, \ldots, x_M^2\}$.

Suppose that there is a target keyword represented by TK_X, and that a certain keyword is represented by x_1, in order to calculate the similarity between the target keyword and the keyword x_1, first calculate the correlation between TK_X and the keyword x_1 on the path XU. The set of TK_X-related text sources and the number of their appearances calculated through the meta-paths XU is defined as $TK\_U = \{u_1{:}V_1, u_2{:}V_2, \ldots, u_K{:}\ V_L\}$, and the set of x_1-related text sources and the number of their appearances is denoted as $x_1u = \{u_1{:}V_1, u_2{:}V_2, \ldots, u_Z{:}\ V_Z\}$, where the number of meta-paths associated with TK_X is denoted as K and that associated with x_1 as Z. Suppose that the text source set of the intersection of TK_X and x_1 meta-paths is $NU = \{TK\_U.K() \cap x_1u.K()\}$, the following formula shows how to calculate the correlation between TK_X and x_1:

$$D(TK\_X, x_1) = 2 * \sum_{u=1}^{NU.L} TK\_U.u * x_1u, u\, (u \in NU) \tag{12}$$

The number of meta-paths through which the keyword TK_X is correlated to the text source u is represented by $TK\_U.u$, and that through which the keyword x_1 is correlated to the text source u by $x_1u.u$. After the correlations of the two keywords through the paths XU are obtained, the similarity between the corresponding keywords can be calculated as follows:

$$R(TK\_X, x_1) = \frac{D(TK\_X, x_1)}{TK\_X^2 + x_1^2} (TK\_X \in X^2 \ \&\&x_1 \in X^2) \tag{13}$$

The correlation between the two keywords is represented by $D(TK\_X, x_1)$, and the sums of the squares of the paths are represented by TK_X^2 and x_1^2. The closer the calculated value of $R(TK\_X, x_1)$ is to 1, the higher the similarity is between TK_X and x_1; and the closer the calculated value is to 0, the lower the similarity is between TK_X and x_1. Figure 4 is a schematic diagram of the similarity clustering result under uneven distribution of text lengths.

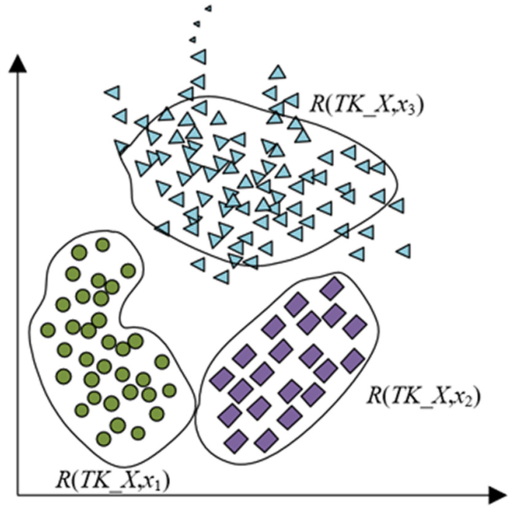

Fig. 4. Schematic diagram of the similarity clustering result under uneven distribution of text lengths

5 Experimental results and analysis

Table 1. Effects of the number of clusters on the clustering performance

Number of Clusters	Indicators			
	Duration of Training by the Algorithm	Duration of Key Sentence Extraction	Duration of Clustering by the Algorithm	Average Distance between Centroids within a Cluster
50	480	109	1.5	8.59
100	480	109	2.6	6.24
150	480	109	2.4	4.27
200	480	109	3.1	3.15
250	480	109	4.9	2.59
300	480	109	4.2	1.58
350	480	109	6.7	1.36
400	480	109	7.1	1.13
450	480	109	11.3	0.75
500	480	109	9.6	0.59

In this paper, the number of clusters was adjusted from 50 to 500. Table 1 shows the text classification result of finance teaching cases under different numbers of clusters. The evaluation indicators for the classification result include duration of training by the algorithm, duration of key sentence extraction, duration of clustering by the algorithm and average distance between centroids within a cluster. It can be seen from the table that the number of clusters had little effect on the duration of training by the algorithm and the duration of key sentence extraction, while with the increase of the number of clusters, the duration of clustering by the algorithm increased, and the average distance between centroids within the cluster decreased.

In order to verify the effectiveness of the proposed long text clustering algorithm for finance teaching cases, comparative experiments were conducted on different data sets. The effectiveness of the algorithm was evaluated by four indicators of text clustering quality of finance teaching cases – homogeneity, completeness, adaptability and normalized mutual information.

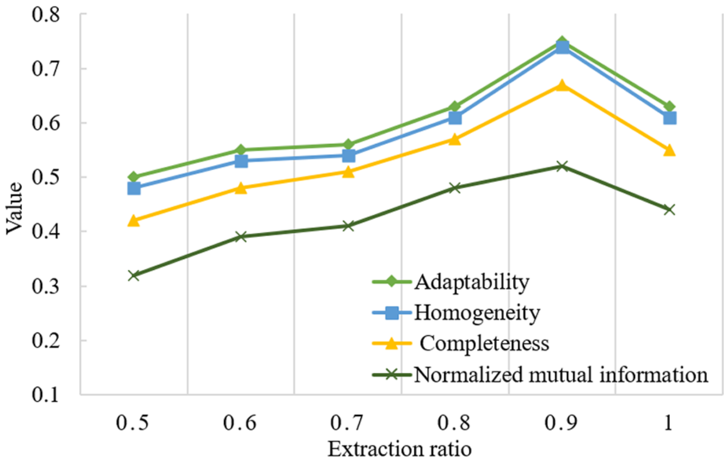

Fig. 5. Effects of the extraction ratio σ on the clustering performance

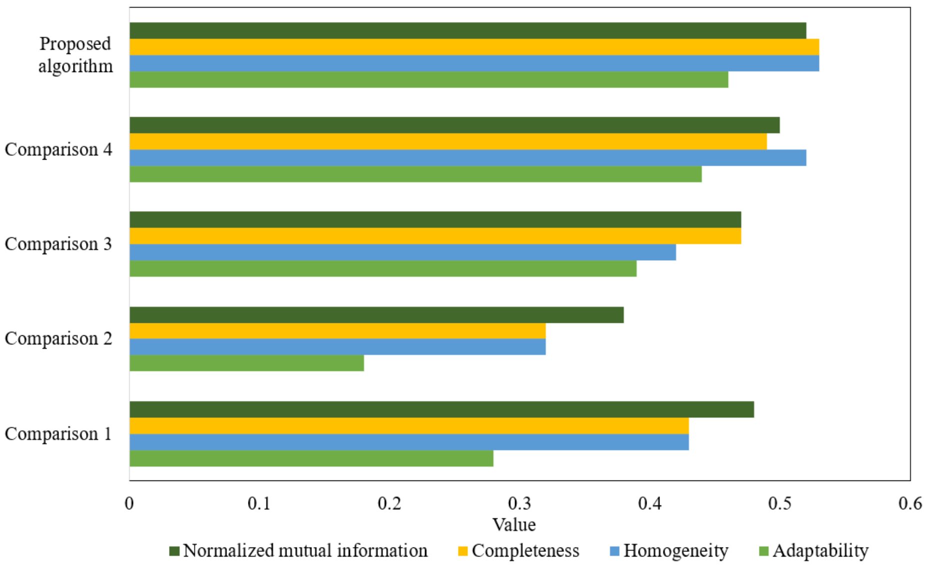

Fig. 6. Comparison of the classification performance of different clustering algorithms

Figure 5 shows the effects of the extraction ratio σ on the classification performance. It can be seen that with the increase of the σ value, the scores of the four evaluation indicators – homogeneity, completeness, adaptability and normalized mutual information – of the proposed clustering algorithm also gradually increased, that is, the classification performance gradually became better. However, when the value of the parameter σ was greater than 0.9, the four evaluation indicators gradually decreased with the increase of the σ value, indicating that the classification performance was getting worse. From the above analysis, it can be seen that, when $\sigma = 0.9$, the proposed clustering algorithm eliminates the interference information and achieves the optimal clustering quality.

Next, the classification performance of different clustering algorithms were compared. The algorithms involved in the comparison included K-means, DBSCAN, DEC and SDCN. It can be seen from the Figure 6 that the K-means algorithm (in comparison 1) had poor classification performance compared with the other algorithms, as the homogeneity, completeness, adaptability and normalized mutual information were all the lowest. The proposed algorithm and SDCN (in comparison 4) had little difference in the values of the four indicators, with the proposed algorithm having only a slight advantage over SDCN. The proposed algorithm also achieved the best clustering quality among all the algorithms, which verified that the proposed algorithm is more suitable for clustering long text of finance teaching cases.

Table 2. Comparison of the classification accuracy of different clustering algorithms

Algorithm	Text set No.	ACC	NMI	ARI	F1
Kmeans	1	0.5273	0.4285	0.2473	0.4857
	2	0.4719	0.2615	0.1527	0.3629
DBSCAN	1	0.7583	0.4362	0.4369	0.6857
	2	0.6295	0.4817	0.4274	0.5328
DEC	1	0.7518	0.5629	0.5182	0.6152
	2	0.6352	0.4352	0.4362	0.5749
SDCN	1	0.7154	0.5174	0.5748	0.6352
	2	0.6295	0.4658	0.4369	0.5284
Proposed algorithm	1	0.7982	0.5784	0.5971	0.7746
	2	0.8027	0.5932	0.6143	0.7341

Table 3. Classification accuracy for different types of teaching case text

Category No.	ACC	NMI	ARI	F1
1	0.7251	0.8492	0.7168	0.8237
2	0.7819	0.7434	0.7042	0.8629
3	0.7263	0.7026	0.7605	0.8547
4	0.8451	0.7519	0.7251	0.8232
5	0.8529	0.7324	0.7638	0.8851
6	0.9264	0.8348	0.9611	0.9162

Table 2 compares the classification accuracy of different clustering algorithms, which was evaluated by four indicators – ACC, NMI, ARI, and Fl. It can be seen from the table that the proposed algorithm could handle text sets from different sources, and achieved the highest scores on the four indicators. Table 3 shows the classification accuracy of the proposed algorithm for 6 different types of finance teaching case text, including cases of financial risk, financial strategy, financial management, financial law, financial relations handling, and financial activity organization. It can be seen that the scores of the four indicators achieved by the proposed algorithm were all greater than 0.7 for 6 different types of finance teaching case text, which was satisfactory.

6 Conclusions

This paper took the teaching cases of online open courses of finance as the object, and studied the classification method for online course teaching cases based on an improved clustering method. First, the text clustering problem of finance teaching cases was described, and the conversion process of the abstracts of the case text and the evaluation method for the importance of words to teaching cases were given. Then, the key sentences were extracted from the text of the finance teaching cases, and the related algorithm was introduced. After that, the clustering flow chart for long texts of finance teaching cases was shown, and the principle of the combined clustering algorithm for finance teaching cases with uneven distribution of long texts and short texts was described in detail. Through experiments, the classification performance of finance teaching case text under different numbers of clusters was shown. Comparative experiments were also carried out on different datasets to verify the effectiveness of the proposed algorithm for clustering long text of finance teaching cases. The classification performance and accuracy of different clustering algorithms were compared, and the classification accuracy of the proposed algorithm with respect to different types of teaching case text was presented, which verified the effectiveness of the proposed algorithm.

7 References

[1] Zaitseva, N.A., Sizova, Z.M., Chauzova, V.A., Larionova, A.A. (2021). Determining the readiness status of university students in STEM education and distance education course. International Journal of Emerging Technologies in Learning, 16(19): 124–138. https://doi.org/10.3991/ijet.v16i19.26047

[2] Han, W., Larson, E.C. (2022). Teaching case: The initial coin offering marketplace: A data analytic case. Journal of Information Systems Education, 33(2): 135–140.

[3] Tezer, M., Orekhovskaya, N.A., Shaleeva, E.F., Knyazeva, S.A., Krokhina, J.A. (2021). The effectiveness of STEM education applied with a distance education approach. International Journal of Emerging Technologies in Learning, 16(19): 180–192. https://doi.org/10.3991/ijet.v16i19.26061

[4] Yao, F., Xu, W., Xu, Z., Wu, Y., Wu, G. (2022). Implementing humanistic view via pass-through game style in teaching: A case study in teaching chemical engineering principles for undergraduates. Education for Chemical Engineers, 38: 48–54. https://doi.org/10.1016/j.ece.2021.07.003

[5] Schwieger, D. (2022). Teaching case: Design and development of a special population resource connection database. Journal of Information Systems Education, 33(2): 141–148.
[6] Zhang, B., Zhang, J., Liu, J., Yue, H., Dong, X. (2022). Teaching reform of single-chip microcomputer experiment course and a case study. In Advances in Guidance, Navigation and Control, pp. 803–812. https://doi.org/10.1007/978-981-15-8155-7_67
[7] Luo, Y., Wang, Z., Zhang, F. (2022). Research on heuristic teaching model based on case comparative experiment. In 2022 11th International Conference on Educational and Information Technology (ICEIT), Chengdu, pp. 1–5. https://doi.org/10.1109/ICEIT54416.2022.9690734
[8] Blumenthal, R. (2022). Teach more, not less computability theory in CS202X: A case for teaching multiple representations of the church-turing thesis. In Proceedings of the 53rd ACM Technical Symposium on Computer Science Education V.1, Providence RI, USA, pp. 675–681. https://doi.org/10.1145/3478431.3499309
[9] Chamkin, A.A. (2022). Teaching cyclopentadienyl how to leave: A case study of the [CpIr (COD) Br]+ complex. New Journal of Chemistry, 46(15): 6847–6851. https://doi.org/10.1039/D2NJ00098A
[10] Dunn, P., Miller, R.E. (2022). Teaching case: Widgets-R-Us: Using IoT to monitor part levels. Journal of Information Systems Education, 33(3): 229–231.
[11] Karamollahi, M., Williamson, C., Arlitt, M. (2022). Zoomiversity: A case study of pandemic effects on post-secondary teaching and learning. In International Conference on Passive and Active Network Measurement, Monterrey, Mexico, pp. 573–599. https://doi.org/10.1007/978-3-030-98785-5_26
[12] Xiao, F. (2022). A new research-based case teaching method for an occupational quality curriculum based on moodle. International Journal of Emerging Technologies in Learning (iJET), 17(9): 67–82. https://doi.org/10.3991/ijet.v17i09.30929
[13] Tureková, I., Marková, I., Sventeková, E., Harangózo, J. (2022). Evaluation of microclimatic conditions during the teaching process in selected school premises. Slovak case study. Energy, 239: 122161. https://doi.org/10.1016/j.energy.2021.122161
[14] Adesso, M.G., Capone, R., Fiore, O. (2022). Inquiring electricity in primary school: A non-formal teaching education case study. In Journal of Physics: Conference Series, 2297: 012022. https://doi.org/10.1088/1742-6596/2297/1/012022
[15] Utomo, M.N.Y., Sudaryanto, M., Saddhono, K. (2020). Tools and strategy for distance learning to respond COVID-19 pandemic in Indonesia. Ingénierie des Systèmes d'Information, 25(3): 383–390. https://doi.org/10.18280/isi.250314
[16] He, X., Yu, K., Huang, Z., et al. (2022). Multilevel-teaching/training practice on GNSS principle and application for undergraduate educations: A case study in China. Advances in Space Research, 69(1): 778–793. https://doi.org/10.1016/j.asr.2021.11.021
[17] Mustapha, R., Soukaina, G., Mohammed, Q. (2022). Towards a connected smart classroom: Case of an adaptive teaching activity. In 2022 2nd International Conference on Innovative Research in Applied Science, Engineering and Technology (IRASET), Meknes, Morocco, pp. 1–5. https://doi.org/10.1109/IRASET52964.2022.9738220
[18] Asef, P., Kalyvas, C. (2021). Computer-aided teaching using animations for engineering curricula: A case study for automotive engineering modules. IEEE Transactions on Education, 65(2): 141–149. https://doi.org/10.1109/TE.2021.3100471
[19] Guo, B.H., Milke, M., Jin, R. (2022). Civil engineering students' perceptions of emergency remote teaching: A case study in New Zealand. European Journal of Engineering Education, 47(4): 679–696. https://doi.org/10.1080/03043797.2022.2031896
[20] Budiarti, M., Ritonga, M., Rahmawati, Yasmadi, Julhadi, Zulmuqim. (2022). Padlet as a LMS platform in Arabic learning in higher education. Ingénierie des Systèmes d'Information, 27(4): 659–664. https://doi.org/10.18280/isi.270417

[21] Hicks, A.L. (2022). The role of community-based learning in teaching about industrial ecology and sustainability in the context of engineering education: A case study from the field. Journal of Industrial Ecology, 26(3): 1136–1146. https://doi.org/10.1111/jiec.13224
[22] Botari, A., Botari, J.C., da Rocha Brito, C., Ciampi, M.M. (2022). Educational tools and interventional analysis of meaningful learning: Case studies applied to teaching acoustic physics in the discipline of environmental comfort. IEEE Revista Iberoamericana de Tecnologias del Aprendizaje, 17(2): 115–124. https://doi.org/10.1109/RITA.2022.3166860
[23] Martins, P., Pinto, A., Costa, E., Abreu, A. (2022). Digital transformation in the teaching and learning process: Case study of a school of the future. In Perspectives and Trends in Education and Technology, pp. 1015–1025. https://doi.org/10.1007/978-981-16-5063-5_83
[24] Yang, B., Jiang, J., Zhao, J. (2021). Case-based classification model based on information diffusion and interval gray relational analysis. Grey Systems: Theory and Application, 12(1): 174–196. https://doi.org/10.1108/GS-08-2020-0115
[25] Liang, Y., Wang, S., Wang, L., Liu, Z., Song, X., Yuan, J. (2022). Classification and application of teaching evaluation text based on CNN and stacked bidirectional LSTM. In International Conference on Adaptive and Intelligent Systems, Qinghai, China, pp. 468–484. https://doi.org/10.1007/978-3-031-06794-5_38
[26] Li, H. (2020). Text recognition and classification of English teaching content based on SVM. Journal of Intelligent & Fuzzy Systems, 39(2): 1757–1767. https://doi.org/10.3233/JIFS-179949

8 Author

Liyang Li, Female, graduated from Lanzhou University of Finance and Economics with a master's degree in accounting, and she is a lecturer in Shijiazhuang University of Applied Technology. Her main research interests are financial accounting and higher vocational education. She has published nine academic papers in recent three years and participate in many skill competitions and win awards

Article submitted 2022-09-10. Resubmitted 2022-10-19. Final acceptance 2022-10-26. Final version published as submitted by the authors.