Research on self-adaptive clustering algorithms for large data sparse networks based on information entropy

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Abstract. With the advent of the era of artificial intelligence and information technology, a large number of data and information pour into all walks of life. These data packages include many online and offline data such as text files, audio and video. However, so many data are unnecessary in real life. The application of data clustering algorithm based on artificial intelligence technology can solve such problems very well. However, the traditional clustering algorithm relies too much on manual operation when choosing clustering centers, which greatly reduces the efficiency of the whole algorithm. At the same time, the traditional clustering algorithm based on sparse network has too many coefficients in its coefficient matrix design, so it cannot aggregate the relevant data well. This paper will measure the correlation of related data based on information entropy, and innovatively improve the existing sparse data network model. A model training algorithm based on multi-strategy pattern optimization is proposed to realize the automatic selection of clustering centers and reduce the training time of the algorithm. In terms of data clustering correlation, this paper proposes an optimized adaptive clustering algorithm based on the joint model of sparse subspace clustering algorithm model and the norm of adaptive subspace segmentation. In the experimental part, this paper compares the proposed algorithm with the traditional density peak clustering algorithm. The experimental results show that the proposed algorithm has obvious advantages in text data collection and classification, image data collection and filtering.

1. Introduction

With the advent of the information age, a large amount of data has flooded into people's lives. These data contain a large number of text documents, video and audio. However, people's demand for these data or useful data for people is limited [1-3]. Therefore, in this context, data mining technology has become one of the core technologies to analyze and classify these massive data. Data mining and classification is to discover and classify the massive data in the database automatically. At the same time, these processed data are used to provide people with information management, information query, information processing and decision-making control. Clustering algorithm is a common algorithm in data mining technology. The core idea of this method is to find and extract useful information from complex databases [4-7]. The traditional clustering algorithm mainly has the density peak clustering algorithm, but it relies too much on manual selection of clustering centers, which greatly reduces the efficiency of the algorithm [8-9]. Based on this, the improved sparse network clustering algorithm has too many coefficients in its coefficient matrix design, so it cannot aggregate...
the relevant data greatly. Therefore, with the explosion of data, the research of improved clustering algorithm is becoming more and more important.

In order to solve the problem of clustering degree and efficiency of clustering algorithm, a large number of scholars have studied and improved clustering algorithm. In 2013, American scholars put forward the concept of adding sparse matrix to clustering algorithm, and proposed a low rank sparse subspace clustering algorithm, which combines the sparseness of sparse matrix and the advantage of low rank [11-12]. In 2015, Lu et al. proposed an adaptive sparse clustering algorithm, which proposed the concept of adaptive subspace segmentation to solve the problem of correlation gluing of sparse matrices in related data processing [13-14]. In the same year in 2015, Patel and other scholars proposed to extend SSC to non-linear based on kernel technology, and then proposed a kernel Sparse Clustering Algorithm [15]. In 2016, British scholars put forward a new viewpoint of clustering algorithm: according to the rigid representation of data processed in the same space, these rigid representations are further evolved into sparse subspace clustering algorithm of self-expression [16-18]. In 2018, Chinese scholars proposed a structured Sparse Clustering algorithm. The main idea is to separate the sparse representation in SSC from the corresponding clustering, and then combine the sparse representation with the corresponding clustering. The sparse matrix is modified by the constraint matrix obtained from the reverse clustering result [19-20].

This paper will measure the correlation of related data based on information entropy, and innovatively improve the existing sparse data network model. A model training algorithm based on multi-strategy pattern optimization is proposed to realize the automatic selection of clustering centers and reduce the training time of the algorithm. In terms of data clustering correlation, this paper proposes an optimized adaptive clustering algorithm based on the joint model of sparse subspace clustering algorithm model and the norm of adaptive subspace segmentation. In the experimental part, this paper compares the proposed algorithm with the traditional density peak clustering algorithm. The experimental results show that the proposed algorithm has obvious advantages in text data collection and classification, image data collection and filtering.

This paper makes the following arrangements on the structure of the article: The second section of this paper mainly introduces the core technology of the related work clustering algorithm and the comparison of the current mainstream literature scholars' research on this algorithm; the third section of this paper will specifically study and analyze the large data sparse network based on information entropy, and concretely analyze the model training algorithm and self-adaptation of the multi-strategy pattern optimization proposed in this paper. The fourth section compares the traditional density peak clustering algorithm with the algorithm proposed in this paper and analyses the data. The last section will make a summary and an outlook of the full text.

2. Relevant research in this paper: research and analysis of clustering algorithms

This section mainly studies and analyses the related theoretical work of the clustering algorithm proposed in this paper, in which the key technologies of the core clustering algorithm are mainly studied and analyzed. At the same time, aiming at the problems existing in the current clustering algorithm, such as the clustering center can not be selected intelligently and the data can not be clustered well, the paper analyses the advantages and disadvantages of the improved algorithm proposed in the current relevant literature.

2.1. Relevant work 1: research and analysis of large data mining technology-clustering algorithms

The core essence of clustering algorithm is that in the absence of any reference and guidance environment, and the marker information learned or trained by the machine is unknown, under such a premise, a large number of data will be classified and analyzed. The main work of clustering algorithm in the process of operation is the similarity calculation algorithm, which is mainly used to measure the similarity between variables. Taking data set $A = (a1, a2, a3, a4, a5..... An)$ as an example, the algorithm foundation of this paper is explained in detail. In the data set $A = (a1, a2, a3, a4, a5..... An)$, the corresponding $x_n = (x1, x2, x3... x_j)$, $Xij$ represents the characteristic attributes of the relevant data,
and it needs to satisfy four conditions when calculating the similarity: symmetry, non-negativity, triangle rule and corresponding reflexivity. The corresponding clustering analysis process is shown in Figure 1.

![Figure 1. The corresponding clustering analysis process.](image_url)

The Euclidean distance between two points in the two-dimensional plane should be calculated in advance when calculating the algorithm similarity based on the above process. The corresponding core calculation formula is shown in Formula 1, where the corresponding a(x1, y1) and b(x2, y2) are any two data points on the corresponding plane:

\[ S_{ab} = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \]  

(1)

The corresponding distance between any three data points in the three-dimensional data space is shown in formula 2.

\[ S_{ab} = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2 + (z_1 - z_2)^2} \]  

(2)

By analogy, the Euclidean distance between two n-dimensional vectors is shown in Formula 3.

\[ S_{ab} = \left( \sum_{i=1}^{n} |x_{ai} - x_{bi}|^{1/2} \right)^2 \]  

(3)

In order to ensure the accuracy of similarity, Pearson correlation formula is introduced to verify the similarity in the process of calculating the similarity of clustering algorithm. The corresponding formula is shown in Formula 4.

\[ S'_{ab} = \frac{(1 - r_{ab})/2}{r_{ab}} = \frac{\sum_{i=1}^{d} (x_{ai} - \bar{x}_a)(x_{bi} - \bar{x}_b)}{\sqrt{\sum_{i=1}^{d} (x_{ai} - \bar{x}_a)^2 \sum_{i=1}^{d} (x_{bi} - \bar{x}_b)^2}} \]  

(4)

Based on the basic preparation of the above algorithm, this section describes the implementation process of the algorithm with specific density peak clustering algorithm. Density peak clustering algorithm is a heuristic algorithm. Its main algorithm implementation process is as follows. The corresponding density peak clustering example distribution chart is shown in Figure 2.

![Figure 2. The corresponding density peak clustering example distribution chart.](image_url)
The first step is to compute the Euclidean distance between any data in the space, and virtual to the data similarity matrix. At this time, the matrix formed should be a diagonal matrix, and its corresponding form satisfies: DIJ = dji.

Step 2: The second step is to calculate the local density of the corresponding data points based on the similarity matrix in the first step and the parameter D input by the relevant input terminals.

Step 3: Calculate the minimum distance between each data point and the high density data point in the whole data system.

Step 4: The fourth step is to form the corresponding decision map, in which the points with larger values of abscissa and longitudinal coordinates are selected as the clustering data center of the clustering algorithm.

Step 5: Fifth step: divide the remaining data points into corresponding cluster centers.

Step 6: Find the noise points.

Based on the above steps, the probability map of data point distribution of data set A can be obtained preliminarily. As shown in Figure 3, it can be seen from the graph that this basic clustering algorithm has shown some distortion when the data is relatively complex, and the cumbersome selection of clustering centers has greatly hindered the efficiency of its algorithm.

2.2. Relevant work 2: analysis and research of current mainstream clustering algorithms

In order to solve the above problems, the current mainstream clustering algorithms mainly focus on the improvement and optimization of density peak clustering algorithm and sparse network clustering algorithm. Based on this, a large number of scholars have studied and improved the clustering algorithm. In 2013, American scholars put forward the concept of adding sparse matrix to clustering algorithm and proposed a low rank sparse subspace clustering algorithm, which combines the advantages of sparse matrix and low rank. In 2015, Lu et al. proposed an adaptive sparse clustering algorithm, which proposed the concept of adaptive subspace segmentation to solve the problem of correlation gluing of sparse matrices in related data processing. In the same year in 2015, Patel and other scholars proposed to extend SSC to non-linear based on kernel technology, and then proposed a kernel Sparse Clustering algorithm. In 2016, British scholars put forward a new viewpoint of clustering algorithm: according to the rigid representation of data processed in the same space, these rigid representations are further evolved into sparse subspace clustering algorithm of self-expression. In 2018, Chinese scholars proposed a structured Sparse Clustering algorithm. The main idea is to separate the sparse representation in SSC from the corresponding clustering, and then combine the sparse representation with the corresponding clustering. The sparse matrix is modified by the constraint matrix obtained from the reverse clustering results. In a word, these improved algorithms can not achieve the balance between training time and clustering correlation.
3. Research and analysis of large data sparse network adaptive clustering algorithm based on information entropy

This section will mainly analyze the two improved strategies proposed in this paper, namely, the model training algorithm based on multi-strategy pattern optimization, the automatic selection of clustering centers and the reduction of training time, and an optimized adaptive clustering algorithm combined with the joint model of sparse subspace clustering algorithm model and the norm of adaptive subspace segmentation. The overall flow chart of the algorithm is shown in Figure 4.

**Figure 4.** The overall flow chart of the algorithm.

3.1. Analysis and research of large data sparse network based on information entropy

In order to representatively process information, this paper innovatively applies information entropy to the data processing stage of the clustering algorithm proposed in this paper. The average value of information contained in information is replaced by information entropy, and its calculation formula is shown in formula 5. The corresponding $X_i$ is a single information point and the corresponding $P(x_i)$ is its calculation function.

$$H(x) = - \sum x_i log p(x_i)$$  \hspace{1cm} (5)

In this paper, the definition of practical application: when the information entropy of a data is larger, the information contained in it is larger, and the uncertainty of the corresponding information is stronger, the information is relatively dispersed; when the information entropy is smaller, the information uncertainty is smaller, and the information is relatively centralized. In this paper, it is assumed that the range of information entropy is [0-logn], where the corresponding n represents the length of distribution probability of information.

Based on the concept of information entropy assumption, a large data sparse network is constructed to provide preliminary preparation for adaptive clustering algorithm. Based on the DBN network model, the large data sparse network is constructed as shown in Figure 5. The corresponding DBN network architecture consists of several RBM architectures. The corresponding upper layer is the input layer, which is mainly used for the training entrance of automatic learning cluster center selection in the later stage. There are many hidden layers between input layer and output layer. DBN sparse network is built in two steps. First, in the unsupervised training stage, the layer-by-layer information entropy construction method trains RBM from top to bottom and forms the corresponding network. At the same time, the first network is chosen as the hidden network of the second network when the next network is built, so the construction is iterated until completion. Second, after all network layers are built, each network is trained and optimized separately until all RBM is trained.
The most critical step in constructing sparse network based on information entropy is the optimization processing part of the network. The main optimization expression is shown in Formula 6, where the corresponding $n$ is the number of actual objective functions.

$$\min F(x) = (f_1(x), f_2(x), \ldots, f_n(x))^T$$

(6)

In order to obtain the optimal target vector and its corresponding optimal target calculation formula, as shown in formula 7, where the corresponding $x$ is the optimal solution. The corresponding front-end diagrams are shown in Figure 6.

$$P = \{x^* \in \Omega \mid \exists x \in \Omega, x > x^*\}$$

(7)

Figure 5. The large data sparse network.

3.2. Model training algorithm for multi-strategy pattern optimization

The multi-strategy pattern optimization model training algorithm proposed in this section is one of the innovations of the whole algorithm in this paper. It mainly solves the problem of low efficiency of the traditional peak density algorithm.

In order to solve the algorithm cost caused by manual selection of clustering centers in traditional peak algorithm, this section intelligently trains the selection of clustering centers based on multi-strategy mode, so as to realize the optimal automatic selection of clustering centers. The corresponding algorithm flow chart is shown in Figure 7.

Figure 6. The corresponding front-end diagrams.
Initialization of SRBM structural parameters, hyperparameters and training cycles

Updating SRBM Data and Structural Parameters Using CD Algorithms

Updating SRBM parameters with the proposed algorithm

Is it up to expectation?

Structural parameters of SRBM

Figure 7. The corresponding algorithm flow chart.

In practical application, the implementation steps of the algorithm are as follows:

The first step is to initialize the structural parameters of the data related to the cluster center. The corresponding updating rules are shown in Formula 8, 9 and 10. The corresponding w represents the structural parameters, and the corresponding a and B represent the corresponding meta-time input data respectively.

\[ w_j = w_j + \varepsilon(<v_j h_j > \rho) - <v_j h_j > \rho) \]  
(8)

\[ a_i = a_i + \varepsilon((v_i \rho) - (v_i \rho)) \]  
(9)

\[ b_i = b_i + \varepsilon((h_i \rho) - (h_i \rho)) \]  
(10)

The second step is to optimize the above structural parameters by using the optimization objective algorithm of sparse network and update them continuously.

Step 3: Repeat the above steps until the whole algorithm converges.

In the optimization selection, the adaptive quantum multi-strategy evolutionary algorithm based on decomposition is the core of the whole multi-strategy pattern optimization training model algorithm. The corresponding objective function formula is shown in Formula 11. In practical application, real coding is used to reduce the storage pressure of the whole algorithm. At the same time, in the actual operation, it mainly judges whether the termination condition of evolution has been reached according to the initialization program (initialization vector, population, domain and reference point), searches for optimization continuously and stops the operation of the algorithm.

\[ \sum_\zeta = \theta = 1 \min ||P|| P_0', \sum_i ||p(h_i || v') || v) \]  
(11)

Based on this algorithm, a validation simulation is done in this section. As shown in Table 1, it is mainly based on the manual self-selected clustering center and the time comparison of the proposed multi-strategy training algorithm on different models.
Table 1. Self-selected clustering center and the time comparison of the proposed multi-strategy training algorithm on different models.

| Sample size | 100  | 500  | 1000 | 2000 |
|-------------|------|------|------|------|
| BRM         | 27.12| 16.78| 12.36| 11.02|
| SR-BRM(0.04)| 28.14| 15.66| 11.21| 7.48 |
| SR-BRM(0.06)| 28.11| 15.21| 10.11| 9.01 |
| SR-BRM(0.08)| 20.11| 13.98| 12.34| 6.35 |
| SR-BRM(0.1) | 27.35| 11.21| 11.34| 7.45 |

3.3. Norm adaptive clustering algorithm based on joint model and adaptive subspace segmentation

In order to improve the relevance of clustering data, this section mainly introduces the second innovation of this paper, that is, norm adaptive clustering algorithm based on joint model and adaptive subspace segmentation.

Traditional subspace adaptive clustering algorithm only pays attention to the norm problem of subspace, but neglects its internal relationship with two-box model. Based on this, this paper combines subspace structure norm and Lasso norm, and makes use of the combination of these two norms and joint model to make coefficient matrix satisfy both diagonal structure and dense relationship between diagonals. The corresponding optimization model is modified as shown in Formula 12, where the corresponding a and B are the corresponding equilibrium parameters.

$$\min \lambda \| X_{Diag}(C_i) \| + \alpha \| C_i \|, s.t. x_i = X_{ci}$$

(12)

According to the corresponding ADMN principle, the corresponding optimization equivalent model can be summarized as shown in Formula 13.

$$\min \frac{H}{2} \| x_i - Xz_i \|^2 + \lambda \| J \|_{q} s.t. J = X_{Diag}(z_i) = c_i$$

(13)

The main algorithm schematic diagram is shown in Figure 8.

Figure 8. The main algorithm schematic diagram.
Step 1: Initialize the relevant input parameters.
Step 2: Main iteration: When the number of iterations of the algorithm does not reach the M set in the algorithm, iteration is carried out continuously. In the iteration process, the sparse optimization model is solved and the corresponding J values are updated continuously. At the same time, the corresponding sparse parameters z, C and Lagrange multipliers need to be updated continuously.
Step 3: Cluster C is solved and Q matrix is obtained.
Step 4: Data output X and classify it.
The corresponding coefficient matrix $C=[c_1, c_2, c_3... c_n]$, which is clustered and partitioned into the corresponding sub-matrix $Q$, uses the new sub-matrix to optimize the model and generate the constraint matrix, and repeats the above process until the number of iterations M is satisfied. After M iterations or convergence of the whole algorithm, the above steps are optimized and the corresponding original and dual residuals are calculated. The corresponding calculation formulas are shown in Formula 13 and the corresponding dual residuals are shown in Formula 14.

$$\|z_i^{k+1} - c_i^{k+1}\|_e < \|z_i^k - c_i^k\|_e$$ (14)

$$\|J^{k+1} - J^k\|_e < \varepsilon$$ (15)

4. Experiments and data analysis
In order to verify the superiority of the proposed algorithm, this paper compares the traditional density peak clustering algorithm with the proposed algorithm. The experimental part is mainly divided into three parts: 1. overall performance analysis, 2. algorithm consumption comparison, 3. data clustering comparison.

4.1. Overall performance analysis and comparison, contrast algorithm: density peak clustering algorithm
Based on the data set A proposed in the second section of this paper, as shown in Figure 9, the corresponding clustering results based on this algorithm and the corresponding clustering results of the density peak clustering algorithm can be seen from the graph that there is no significant difference in the simple data set A.

As shown in Figure 10, the clustering results based on spiral dataset are more uniform, while the clustering results based on density peak clustering algorithm are divergent.

Figure 9. The corresponding clustering results based on this algorithm.
4.2. Experiments of algorithmic consumption

In order to verify the superiority of the multi-model optimization training proposed in this paper, the experiment is based on the traditional density peak clustering algorithm in the manual selection of clustering centers error rate and selection time.

As shown in Fig 11, the corresponding experimental results show that the proposed algorithm has a small error rate.

Table 2. The comparative table of the corresponding time consumed in the experiment sample.

| n    | 100   | 200   | 300   | 400   |
|------|-------|-------|-------|-------|
| 1000 | 1.33  | 1.4   | 1.44  | 1.52  |
| 5000 | 1.63  | 1.66  | 1.67  | 1.89  |
| 10000| 1.82  | 1.87  | 1.98  | 1.23  |
| 60000| 2.24  | 2.4   | 2.77  | 3.24  |
Table 2, cont

| 600 | 700 | 800 | 900 | 1000 |
|-----|-----|-----|-----|-----|
| 1.55 | 1.66 | 2.33 | 1.89 | 1.78 |
| 1.54 | 1.74 | 1.89 | 1.82 | 1.81 |
| 1.98 | 1.92 | 1.97 | 2.01 | 2.09 |
| 3.42 | 3.54 | 3.21 | 4.09 | 4.23 |

### 4.3. Experimental analysis on clustering of algorithms

In order to solve the problem of clustering degree of related data, this experiment is based on the error of clustering degree of data, and the experimental comparison algorithm is still the peak density clustering algorithm.

As shown in Table 3, the error rates of the two algorithms are 100, 2000 and 300 iterations respectively. From the table, we can see that the algorithm proposed in this paper has strong superiority.

| Algorithm    | X1   | X2   | X3   |
|--------------|------|------|------|
| this paper   | 6.66 | 61.1 | 41.23|
| CASS         | 3.30 | 50.67| 20.10|
| SSC          | 2.31 | 3.44 | 1.10 |
| ASSC         | 3.12 | 3.21 | 0.12 |
| density algorithm | 4.90 | 0   | 0   |

The corresponding error polygon is shown in Figure 12.

![Figure 12. The corresponding error polygon.](image)

From the above analysis, we can see that the sparse network adaptive clustering algorithm based on information entropy proposed in this paper has strong advantages.

### 5. Conclusions

In this paper, information entropy is used to measure the correlation of related data, and the existing sparse data network model is innovatively improved. A model training algorithm based on multi-
strategy pattern optimization is proposed, which realizes the automatic selection of clustering centers and reduces the training time of the algorithm. In terms of data clustering correlation, this paper proposes an optimized adaptive clustering algorithm by combining the joint model of sparse subspace clustering algorithm model with the norm of adaptive subspace segmentation. In the experimental part, this paper compares the proposed algorithm with the traditional density peak clustering algorithm. The experimental results show that the proposed algorithm has obvious advantages in text data collection and classification, image data collection and filtering.

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