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DMA Partitioning Method for Water Supply Network Based on Density Peak Optimized Spectral Clustering

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Abstract. *In order to make the pipe network partitioning algorithm of spectral clustering determine the number of partitions based on the pipe network data, this paper uses the ability of density peak clustering (DPC) algorithm to quickly determine cluster center and cluster number, and proposes a simple and effective district metered area (DMA) partitioning method of pipe network. Firstly, the pipe network data is used to calculate the local density and relative distance of all nodes in the pipe network feature space to obtain the pipe network decision graph. Then, the density peak and the number of partitions are determined by the pipe network decision graph, and the regions of pipe network nodes are divided. Finally, the location of water meter and valve is determined according to the density peak of each area and water source, so as to get the final DMA partition scheme of pipe network. The experimental results show that the method is feasible and can determine the number of partitions according to the pipe network data, and the structural modularity of the pipe network partition result is higher than that of the traditional method, and the pressure uniformity is also at a higher level.*
Keywords: Water supply network; Density peak; Spectral clustering; District metered area

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1. **Introduction.** Water supply network is the "water artery" of the city, which plays an important role in ensuring the stability of people's life and the healthy development of the city. With the acceleration of urbanization, the length and scale of urban water supply network are more ambitious and the structure layout is more complex, which makes the operation and management of water supply network more difficult, and the pipe network leakage is easy to occur, resulting in significant economic losses and adverse social impact. The partition of water supply network is the most effective way to control the leakage of water supply network. The "divide and rule" water supply network management idea is widely used. The complex pipe network leakage detection and location task is decomposed into each area, and the leakage location is tracked by the method of minimum night flow or acoustic detection, so as to proactively control the leakage and reduce the difficulty of management and the amount of leakage. At present, water supply network partitioning mainly includes district metered area (DMA) and pressure management area (PMA) [1]. Among them, PMA partition is based on reducing the average pressure of pipe network and focuses on pressure control, which is easily restricted by geographical environment and administrative division. DMA partition is a specific location in the current network after the installation of water meter, valve, the formation of multiple independent regions with permanent boundary, monitoring and analysis of the regional flow, quantify the leakage level of each partition and key maintenance for leakage is the most serious areas, carry out scientific management network, the greatest extent improve the efficiency of pipeline leakage detection, is widely used in practical engineering [2, 3, 4].

The traditional DMA partition mainly relies on manual experience and lacks theoretical support, and the design of each pipe network partition scheme needs a lot of manpower, material resources and financial resources. In view of this, scholars have been exploring more scientific and effective methods to partition water supply network. Perelman et al. [5] partitioned the pipe network topology and determined the connection relationship between the strongly and weakly connected graphs through depth-first search and breadth-first search algorithms, so as to obtain the partition structure with upstream and downstream relationships. Diao et al. [6] used the module degree greedy algorithm based on fast iteration to partition, which can get the pipe network structure with tight internal connections and sparse external connections. Liu et al. [7] applied spectral clustering algorithm to pipe network partition, used genetic algorithm to optimize K-means initial clustering center to achieve pipe network node clustering, and then determined the location of inlet water points according to PageRank and shortest path algorithm, which could achieve different scale partition design. Li et al. [8] compared the depth first search-part of the close degree algorithm, a fast iterative module of the greedy algorithm and genetic optimization partition properties of spectral clustering algorithm, the experiment found that the partition algorithm based on the spectral clustering has the characteristics of wide applicability, good performance, high modularity, the number of nodes in the region is balanced, and the number of boundary pipelines is small, etc.

The water supply network partitioning method based on spectral clustering can fully exploit the clustering information of the pipe network feature space and effectively constrain the number of boundary pipe, so it is recognized by scholars and widely used in the pipe network partitioning. Herrera et al. [9] used the pipe diameter and elevation difference as the weight of the edge to construct the similarity matrix, and used the spectral clustering algorithm to divide the similar pipe network nodes to realize the pipe network partition, but the number of partitions needed to be manually determined. Han et al. [10] used spectral clustering and genetic algorithm to iteratively optimize the initial positions of pipe network nodes, so as to optimize the DMA partitioning scheme, but still could not automatically determine the number of partitions. Nardo et al. [11] based on the spectral clustering algorithm used the topological and geometric information of the network layout to complete the partitioning, in which the number of partitions was determined by the eigengap [12], but mainly for the pipe network with obvious difference in the eigenvalue interval.

In conclusion, the partitioning algorithm based on spectral clustering can partition pipe network quickly, but there are shortcomings in the determination of the number of partitions. In this paper, the density peaks clustering (DPC) [13] algorithm is introduced to optimize the spectral clustering partition. The advantage that the density peaks clustering algorithm can determine the number of clusters makes up for the shortage that the spectral clustering partition algorithm can not accurately determine the number of partitions, and the location of water meter and valve can be determined by the density peaks of each partition. It is expected to realize a simple and effective DMA partitioning method for water supply network.

2. Basic Principles.

2.1. Spectral clustering algorithm.

Based on the theory of spectral graph partition, spectral clustering algorithm transforms the clustering problem into the optimal graph partition problem for solving. The algorithm uses the eigen-decomposition of Laplacian matrix to obtain the projection of each data sample in the low-dimensional feature space, and maps n samples to the feature space composed of c feature vectors to approximate the essential characteristics of the sample set, and then complete the data sample partition through K-means algorithm, and the graph partition results usually have less number of cut edges.

The main steps [14] of spectral clustering algorithm are as follows:

(1) Construct the similarity matrix A.

$$A_{n\times n} = \begin{cases} w_{ij} & , \quad (i,j) \in E_{ij} \\ 0 & , \quad (i,j) \notin E_{ij} \end{cases} \tag{1}$$

where w_{ij} is the similarity between endpoints i and j of edge E_{ij} ; n is the number of nodes.

(2) Compute the normalized Laplacian matrix L_{sym}.

$$L_{sym} = D^{-\frac{1}{2}} L D^{-\frac{1}{2}} = I - D^{-\frac{1}{2}} A D^{-\frac{1}{2}} \tag{2}$$

where D is the degree matrix; A is the similarity matrix; $L = D - A$,denotes the standard Laplacian matrix of the graph; I is the identity matrix.

(3) The eigenvectors corresponding to the first c smallest eigenvalues of L_{sym} are obtained by eigen-decomposition, and a new matrix X is formed according to columns. The row vectors of X are converted into unit vectors, and the eigenspace $Y_{n\times c}$ composed of n c-dimensional feature nodes is obtained.

(4) The nodes of feature space $Y_{n\times c}$ are clustered by K-means algorithm, and then mapped to the original data to realize the clustering and segmentation of the graph.

2.2. DPC algorithm.

Data mining technology with the concept of clustering can quickly find the potential classification information in the data set [15]. DPC algorithm is a density-based clustering algorithm, which has the advantage that it can quickly determine the center of the cluster and the number of clusters in any shape dataset. The center of the cluster in this algorithm satisfies the following two characteristics:

(1) The local density of cluster centers is large, and the cluster centers are far away from each other.

(2) Low-density nodes surround high-density nodes.

In order to find the density peak (cluster center) satisfying the above characteristics, the DPC algorithm introduces two parameters: local density ρ and relative distance δ. The local density ρ_i of data point i includes two ways: the cutoff kernel (Equation 3) and the gaussian kernel (Equation 4).

$$\rho_i = \sum_{i \neq j} \chi(d_{ij} - d_c) \tag{3}$$

$$\rho_i = \sum_{i \neq j} \exp\left[-(\frac{d_{ij}}{d_c})^2\right] \tag{4}$$

where d_{ij} is the distance between point i and point j in the data set; d_c is the cutoff distance, which needs to be manually specified; $\chi(x)$ is a piecewise function, $\chi(x) = 1$ when d_{ij} is less than d_c, and $\chi(x) = 0$ otherwise.

The relative distance δ_i is the distance between sample point i and its nearest and denser sample point j. Where, the relative distance of the highest point of density is the maximum distance between this point and other sample points, as defined in Equation 5.

$$\delta_i = \begin{cases} \min\limits_{j:\rho_j > \rho_i} (d_{ij}) & , \quad \rho_i < \max(\rho) \\ \max\limits_{i \neq j}(d_{ij}) & , \quad \rho_i = \max(\rho) \end{cases} \tag{5}$$

In view of the large local density and relative distance of the density peak, the density peak and its quantity can be determined by constructing a decision graph with ρ as the abscissa and δ as the ordinate.

3. Methodology.

3.1. DMA Partitioning Steps.

The traditional spectral clustering method for water supply network partitioning uses K-means algorithm to cluster nodes in feature space. In the clustering process, the number of cluster centers should be specified in advance and the cluster center of feature space should be determined [7]. Among them, K-means algorithm divides clusters according to distance, which is suitable for mining spherical clusters and difficult to determine the number of partitions. However, the distribution shape of nodes in pipe network feature space is complex and diverse, which is more suitable for node clustering according to the degree of density. Therefore, DPC algorithm is selected for feature space clustering, and the number of pipe network partitions can be determined at the same time.

The steps of the proposed network partitioning method can be summarized as follows:

Step1: The similarity matrix is constructed according to the hydraulic data of pipe network, and then the pipe network feature space $Y_{n \times c}$ is obtained through Equation 2.

Step2: According to the decision graph, the points with larger local density ρ and relative distance δ in the pipe network feature space are selected as the initial clustering points to determine the number of pipe network partitions, and then the remaining nodes are allocated to get the clustering results of pipe network nodes.

Step3: Each density peak corresponds to a partition, and the location of the water meter and valve is determined according to the shortest path of the weight between the density peak of each zone and the water source point, forming the final DMA partition result of the pipe network.

3.2. **Construction of Similarity Matrix.** The construction of similarity matrix is the first step of pipe network partitioning. Different similarities express different data features. Therefore, the selection of similarity will affect the node distribution of pipe network feature space. There is a water supply network topology $G = (V, E)$, where $V = \{v_1, v_2, ..., v_n\}$ represents the information of all nodes in the pipe networks, and the corresponding information includes node number, pressure and water demand, etc. $E = \{e_1, e_2, ..., e_m\}$ represents the information of all pipe in the pipe networks, each edge e_i corresponds to a pair of nodes (v_i, v_j), whose value can represent flow rate, pipe diameter and pipe length, etc.

This paper uses the information of pipelines and nodes at the same time, and takes the average pressure acting on the nodes at both ends of the pipeline and the relative size of the pipe section area as the similarity between nodes, which can reflect the stress status of each pipeline of the pipe network. The smaller its value is, the smaller the probability of pipeline leakage. w_{ij} is calculated as follows:

$$w_{ij} = \frac{P(i) + P(j)}{2\pi r_{ij}^2} \quad , \quad ij \in E \tag{6}$$

where $P(i)$ and $P(j)$ are the pressure of the nodes at both ends of pipeline e_{ij}; r_{ij} is the radius of the pipeline e_{ij}.

3.3. **Clustering of Pipe Network Nodes.** The pipe network similarity matrix A is transformed into the normalized Laplacian matrix L_{sym}, and the matrix L_{sym} is eigen-decomposed, and the first c eigenvectors with smaller eigenvalues are selected to form the matrix $Y_{n\times c}$. The matrix $Y_{n\times c}$ represents the pipe network feature space, and the c values in each row represent a data node of the original pipe network. The local densities and relative distances of all nodes in the pipe network feature space are calculated to obtain the pipe network decision graph. Then, the point with larger local density and relative distance is selected from the decision graph as the density peak, and the number of points is the number of pipe network partitions. Each density peak corresponds to a DMA partition, and the remaining nodes are assigned to the DMA partition whose density is larger than that and where the nearest density peak is located, so as to obtain the pipe network node clustering result.

3.4. **Determine the Location of the Water Meter and Valve.** The boundary pipeline refers to the pipe connecting different partition in the pipe network. After the clustering results of pipe network nodes are obtained, the locations of water meters and valves need to be determined on the boundary pipeline to form the final DMA partition scheme.

The density peak of each partition is the most representative point in each partition of the pipe network feature space, which can be regarded as the key node. Compute the shortest path of weight between the water source point and the key node of each partition, find the pipeline intersecting the path in the boundary pipeline set as the installation position of the water meter, ensure that there is at least one inlet pipe in each partition, and install valves in the remaining boundary pipelines.

The specific steps are as follows:

Step1: Obtain the density peak of each DMA partition and the location of each water source in the pipe network.

Step2: The inverse of the flow was used as the weight to record the shortest path of weight between each density peak and the water source.

Step3: The boundary pipeline in the shortest path is set as the inlet pipe, and the other boundary pipeline are all closed.

Step4: The hydraulic simulation software is used to simulate the running status of the pipe network under the current state. If the simulation fails, return to Step 3, and then open the closed pipeline with a large flow weight and continue the simulation.

Step5: The simulation is successful, and the position of pipe network water meter and valve can be obtained.

4. **Case Study.**

4.1. **Partition Evaluation Index.**

In order to verify the reliability of the water supply network partitioning method proposed in this paper, the following two partition evaluation indexes are used [16]:

(1) Structural modularity

The water supply network is regarded as a network composed of k "communities", and different DMA partition represent different communities. The formula to measure the modularity of the community structure of the pipe network is as follows:

$$F_Q = \sum_{C=1}^{k}\left[\frac{W_C}{W} - \left(\frac{S_C}{2W}\right)^2\right] \tag{7}$$

where F_Q is structural modularity; W is the sum of weight of all pipelines; W_C is the sum of the weights of all pipelines whose nodes are completely in partition C; S_C is the sum of the weights of boundary pipelines in partition C.

The better the community partition, the higher the corresponding modularity, which means that the DMA partition scheme is better in partition structure and more reliable in partition result. The modularity has the value in the range of $0 \leq F_Q < 1$.

(2) Pressure uniformity

Whether the node pressure level after the pipe network partition meets the requirements is one of the criteria to measure the quality of the partition scheme. The better the pressure balance of each partition, the higher the stability of the pipe network water supply. The calculation formula is as follows:

$$F_{PU} = \sum_{C=1}^{k}\frac{SU_C}{SU_T}\frac{\sqrt{\sum_{i=1}^{N_C}(PU_{i,C} - PU_{av,C})^2}}{PU_{av,C}} \tag{8}$$

where F_{PU} is pressure uniformity; k is the number of partitions; N_C is the number of nodes in partition C (except the water source point). $PU_{i,C}$ is the water pressure of node i in partition C; $PU_{av,C}$ is the average water pressure in partition C; SU_C is the total water consumption of partition C; SU_T is the total water consumption of the pipe network.

The pressure uniformity reflects the cumulative deviation degree of water pressure in all zones of the pipe network after DMA partitioning. The smaller F_{PU} is, the more balanced the pressure distribution in each zone of the DMA partitioning scheme is.

4.2. **Case Application of Pipe Network.**

Taking Balerma irrigation network [17] as benchmark network, this paper verifies the effectiveness of DMA partitioning method for water supply network based on density peak optimization spectral clustering. The pipeline network includes 447 nodes (443 water demand nodes and 4 water source nodes) and 454 pipelines. Algorithm verification is based on EPANET-MATLAB Toolkit [18], and the pipe network is loaded into MATLAB to perform partitioning.

In the partitioning process of water supply network based on density peak optimization spectral clustering, the number of feature vectors c and the value of a cutoff distance d_c of DPC algorithm will affect the selection of density peak points in the feature space of pipe network. For the pipe network case of Balerma irrigation network, different parameter values are used to observe the pipe network decision graph. Compared with other parameter settings, when the number of feature vectors is set to 4 and the cutoff distance is in the top 8% position, the local density and relative distance corresponding to the peak density are both large.

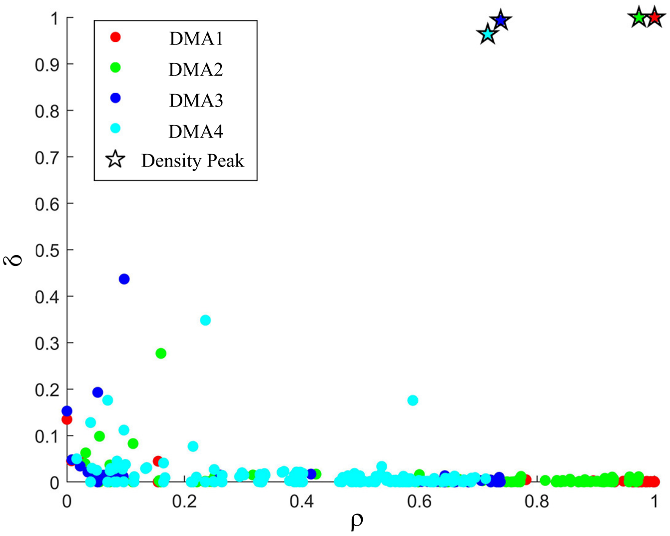

Figure 1. Decision graph of water supply network in the Balerma irrigation network

The four points in the upper right corner of the decision graph of the Balerma irrigation network are significantly different from the rest in Figure 1, and can be used as density peaks, so the number of network partitions is 4. Each partition corresponds to a density peak, and then the remaining points are sequentially allocated to get the pipe network node clustering result. The location of the water meter and valve is determined according to the shortest path of the weight between the density peak and the water source, and the final DMA partitioning scheme of the pipe network is shown in Figure 2.

The partition scheme uses a total of five boundary pipelines to divide the Balerma irrigation network into four DMA partitions. Each DMA partition has an independent water source, making it easier to manage the water supply system in the event of a pipe network failure. EPANET is used to numerically simulate the pipe network DMA partitioning results under different clustering algorithms, and then the structural modularity and pressure uniformity are calculated according to the simulation results, so as to find the advantages of the pipe network DMA partitioning method based on density peak optimization spectral clustering over traditional spectral clustering.

Table 1. Partition evaluation index

State of water supply network		Structural modularity	Pressure uniformity
Original water supply network		1	6.782
After the partition	Based on the DPC	0.974	3.235
	Based on the K-means	0.972	3.235

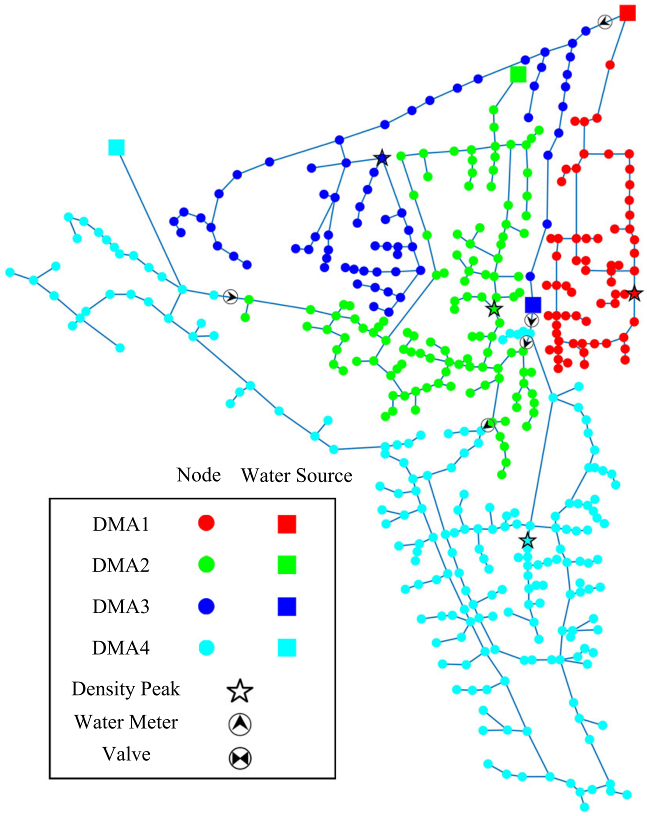

FIGURE 2. DMA partition scheme of water supply network in Balerma irrigation network

As can be seen from the analysis in Table 1, the structural modularity of the pipe network partition results are all higher, and the structural modularity of the pipe network partition results based on the DPC algorithm is more higher, indicating that the structural division of the pipe network partition results by the DPC algorithm is more reliable. The pressure uniformity of pipe network partition results based on DPC algorithm is 52.3% higher than that of the original pipe network, while that of the traditional method is also 52.3%. It indicates that the cumulative deviation degree of water pressure can be kept at a low level after the pipe network partitioning using this method, and the pressure in each zone is more balanced, and the effect is not inferior to the traditional method. Figure 3 shows the comparison of node pressure before and after the pipe network partitioning.

It can be seen from Figure 3 that the pressure deviation at each node before and after partitioning is small, which is due to the small number of boundary pipelines in the current benchmark network. Among them, the boundary pipe sections are all water meters, and no pipes are closed, so the pressure is basically unchanged, and they are all within the normal floating range. Thus, it is shown that the DMA partitioning method proposed in this paper has a good partition effect, and the installation of water meters and valves will not have a great impact on the pipe network. It is a simple and effective method that can automatically determine the number of partitions and obtain a better partition result.

5. **Conclusion and Prospect.** In this paper, the ability of DPC algorithm to quickly determine the cluster center of arbitrary shape dataset and the number of the cluster is used, and a DMA partitioning method of water supply network based on density peak optimization spectral clustering is proposed. The number of pipe network partitions and the location of water meter and valve can be determined by density peak to get the final

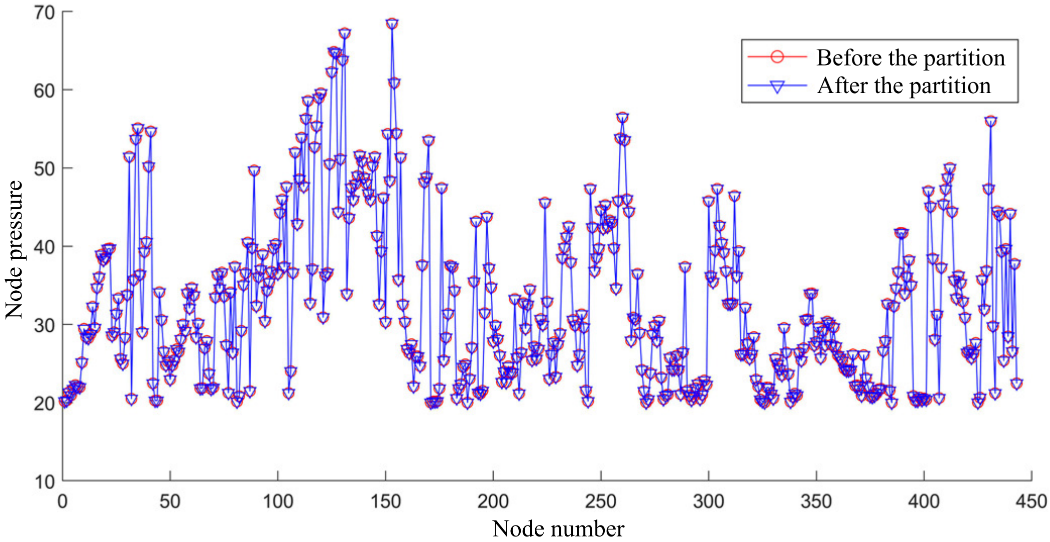

FIGURE 3. Comparison of node pressure before and after the pipe network partitioning

pipe network DMA partition result, which is verified by a real pipe network case. The results show that the proposed method clusters the nodes in the feature space of the pipe network according to the density, and focuses more on the improvement of the structural modularity than the traditional method, which makes the similarity of the nodes in the same partition of the pipe network is high, while the similarity of the nodes in different partitions is low.

In the process of partitioning, the number of feature vectors c and the cutoff distance d_c are the main parameters that affect the result of pipe network partitioning.The method avoids the complex parameter optimization problem with the help of the pipe network decision graph, reduces the amount of calculation, and can quickly obtain the partition results, which is a simple and effective DMA partitioning method. The next step is to use swarm intelligence optimization algorithm to optimize the multi-objective optimization problem of parameters in the process of pipe network partitioning. Among them, the algorithms with better optimization performance include: grid-based multi-objective optimization method (called GMPSO) [19], adaptive intelligent single particle optimization method [20], the improved wolf pack algorithm [21, 22] and the improved firefly algorithm [23, 24, 25], etc.

After the pipe network DMA partition scheme is determined based on the above research results, the functions of the pipe network can be further expanded, and the uncertain measurement and prediction of the data of each water meter in the pipe network can be realized by combining the Internet of Things technology and the deep learning method [26, 27]. The real-time time series data generated by the water meter during the operation of the network can be used to predict, identify and locate the possible leakage location. In the dynamic time series data, the better prediction algorithms include Quantum Genetic Algorithm - Learning Vector Quantization (QGA-LVQ) neural network [28] and the improved LSTM [29, 30]. At the same time, transfer learning technology can be used to accelerate the progress of training the model [31].

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