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Analysis of Parenting Stress, Co-parenting Level, Family Intimacy and Adaptability on Children's Social Skills via self-attention Network

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Abstract: - This paper uses the self-attention method to track family intimacy. We propose the Self-Attention Adversarial Deep Subspace Clustering Algorithm (SAADSC). The self-attention adversarial network is used to impose a prior distribution constraint in the feature learning of the autoencoder, which guides the learned feature representation to be more robust, thereby improving the clustering accuracy. The results show that the proposed algorithm outperforms the state-of-the-art methods in terms of accuracy (ACC) and standard mutual information (NMI). Therefore, we can effectively transfer this self-attention method to the analysis of the effects of adaptation on children's social skills.

Keywords: Self-Attention, Children's Social, Family Intimacy.

I. INTRODUCTION

Family function is an important indicator to maintain the normal operation of the family system and affect the mental health development of family members. Two family functions are included in the whole family system: intimacy and adaptability. Intimacy refers to the mutual encouragement and closeness between family members; and adaptability, also known as flexibility, refers to the satisfaction of family members in family life. The different rules and roles of [1-2]. Family functions play an important role in the physical and mental development of early childhood. Positive family functions can promote children's development, while negative family functions can hinder children's physical and mental health. Social skills refer to an important ability for children to properly and reasonably interact with family members and peers in homeschooling. Some researchers believe that self-control and initiative are important indicators to measure the differences in the development of Chinese children's social skills [3-4]. In the context of collectivism, in order to enhance the cohesion of the group, individuals are often required to suppress personal interests to meet the needs of the collective. Old research found that there are differences in the initiative of Chinese and Western children [5-6]. Chinese children's initiative is related to early-formed attachment styles. Children with secure attachment styles are more proactive, while children with other styles tend to show reluctance to contact others. Chinese children show more sociality than American children. Withdrawal phenomenon.

Parenting style may be an important mediating variable of family intimacy and adaptability affecting children's social skills [7-8]. The results of cross-cultural research show that in different ethnic backgrounds, parents adopt harsh ways to raise children, which can lead to anti-social tendencies in children. Such children are highly aggressive, unwilling to interact with others, and unable to restrain themselves. behavior, and family relations are not harmonious. In the early childhood stage, the type of parenting style will have different effects on the development of children's initiative. Parents' unconditional support for children is conducive to cultivating children's initiative and promoting their autonomous development. In special family backgrounds, such as military families, Both parents and children have a very high sense of identity, but the control status of parents over their children is low, which will lead to less initiative in children's peer interaction.

There is a mediation effect between them. Most of the studies have adopted a cross-sectional approach to examine the social skills, family intimacy and adaptability of children at different ages, as well as parenting styles [9-10]. However, none of these studies considered child development from a longitudinal perspective. Especially in the early childhood, children are in the stage of rapid development. The researcher [11] found that the social skills development of children aged 4 to 5 showed a non-linear growth pattern. For infancy children, as time goes on, the mother shows more encouragement, and the stronger the child's initiative to participate in the game, the better the

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attachment relationship between mother and child; on the contrary, excessive punishment from the mother will make the child withdrawn, it is easier to cry and make a scene, and it is difficult to control.

In recent years, scholars from various countries have found that although the structure of high-dimensional data is difficult to cluster in the entire data space, the internal structure of high-dimensional data is usually smaller than the actual dimension, and the cluster structure may be easily observed in a certain subspace [12-13]. Therefore, in order to cluster high-dimensional data, subspace clustering (SC) assumes that the high-dimensional space can be divided into several low-dimensional subspaces, and then divides the data points extracted from these low-dimensional subspaces into different clusters [14-15]. There are currently four main categories of subspace clustering: the subspace clustering based on spectral clustering has received extensive attention once it was proposed. The basic idea is to first calculate the similarity between data points to construct a similarity matrix, and then The spectral clustering algorithm is used to obtain the final clustering result [16-17]. Two of the most successful subspace clustering algorithms are: Sparse subspace clustering (SSC), [18] forces each data by norm regularization to be as sparse as possible with other data points in the same subspace Representation, and then use the representation coefficient to build a similarity matrix, the obtained similarity matrix can capture the local structure of the data: low-rank subspace clustering (Low. rank representation, LRR), [19] obtain data through nuclear norm regularization the lowest rank representation of, the similarity matrix obtained in this way has the global structure information of the data. Both of these two algorithms use the data "self-representation" mechanism to effectively describe the subspace structure of the data.

On the other hand, with the development of neural networks, Autoencoders (AEs P) have become a popular feature learning method. It encodes the original data into a low-dimensional code through the encoder, and then reconstructs the low-dimensional code back to the original data through the decoder. This low-dimensional encoded data can be regarded as a low-dimensional representation of the original data. In 2006, [20] improved the autoencoder and proposed the deep autoencoder (DAE). Compared with the autoencoder, the DAE with deeper network depth can obtain more robust data representation. After that, proposed DAE to further improve the robustness by adding noise to the data. In order to remove redundant information of data and obtain sparse data representation, proposed sparse auto-encoder (Sparsle auto-encoders, SAE). Replaced the fully connected layer network of encoder and decoder with convolutional neural network and proposed Stacked convolutional autoencoders (CAE) to reduce the amount of network parameters. Based on the advantages of the autoencoder network in feature learning, some researchers have combined it with the clustering [Stork] algorithm: for example, deep embedded clustering (DEC), deep learning and clustering algorithms at the same time (Simultaneous deep learning and clustering, DCN), deep continuous clustering (DCC) and proposed a deep density-based image clustering algorithm (Deep density-based image clustering, DD c) and semi-supervised deep embedding Clustering (semi-superviseddeep embedded clu8tering, SDEC) and so on. Although the above methods improve the clustering accuracy to some extent, how to effectively mine the subspace structure of the data and obtain a more robust data representation still needs further research.

Therefore, this paper proposes a deep subspace clustering method based on white attention adversarial mechanism. In a deep autoencoder network including a "self-representative" network layer, we introduce a white attention mechanism to capture important feature information, and use an adversarial network to enhance the robustness of feature learning. Thus, a better data subspace structure is learned and better clustering results are obtained. In summary, the main contributions of this paper are: 1) propose an algorithm to improve subspace clustering using an adversarial mechanism, making the feature representation learned by the encoder more robust; 2) introduce a self-attention model to solve the clustering problem The long-distance dependence problem of feature learning in class analysis; 3) Experiments show that the self-attention model can effectively model parenting pressure and family intimacy at the level of co-parenting. Our method has great performance compared to the baseline.

II. RELATED WORK

A. Family Intimacy and Adaptability Scale

The family adaptability and cohesion eValuation scales (2ndedition, FACESII) was used to measure the emotional connection between family members and the ability of the family to make changes in response to problems at different developmental stages of the family. The scale was revised by Lipeng et al. It has good reliability and validity. The scale consists of two dimensions, intimacy and adaptability, with a total of 30 items. Using a 5-point scale, with 1 for "no" and 5 for "always", the actual feeling and ideal situation scores of intimacy and adaptability are calculated separately. The higher the total score of the two dimensions, the better the family intimacy and adaptability. The Cmnbach d coefficient of this scale in this study was 0.83.

B. Questionnaire on parenting style

Parenting styles were assessed using the Q-category of child rearing behavior developed by [21]. Research results: 2 journals found that this questionnaire is also applicable to the Chinese population. The questionnaire includes 9 dimensions, namely, acceptance of warmth, punishment, guidance and attribution, control, social encouragement, achievement encouragement, independence encouragement, filial piety training, and doting and protection, with a total of 69 items. A 5-point scale was used, with 1 indicating "completely disagree" and 5 indicating "completely agree". The higher the scores of each dimension, the more inclined parents are to this parenting style. In this study, two dimensions of independent encouragement and punishment were selected, and the Cronbach d coefficients of these two dimensions were 0.71 and 0.63, respectively.

C. Early Childhood Social Skills Questionnaire

The questionnaire divides social skills into two dimensions: initiative and self-control. The questionnaire consisted of 32 questions, which were filled out by either the father or the mother. A 5-point scoring system is used, with 1 being "completely inconsistent" and 5 being "completely consistent". The total score of the scale is summed up in two dimensions. The higher the score, the better the mastery of social skills. The questionnaire was administered twice to the tracked children. In this study, the Cronbach's d coefficients in the T1 and T2 time periods were 0.91 and 0.93, respectively.

D. Self-Attention Model

At present, most attention models are embedded in the encoder-decoder framework. Usually, when a high-dimensional data is encoded to output a low-dimensional feature representation, a lot of information will be lost. The attention model can weight and average different data information, so the encoder-decoder framework containing the attention model will encode a Low-dimensional feature representation with less information loss. The mathematical expression of the attention model is as follows:

$$Attention(Q,K,V) = s(Q,K^T)V \quad (1)$$

In this model, K,V comes from the input information like the ordinary attention model. On the other hand, in order to directly capture the correlation between any two vectors in the input data matrix, Q also comes from the input information. However, the attention model is not limited to the encoder-decoder framework. For example, the self-attention model is introduced into the generative adversarial network in Self-attention generative adversarial networks (SAGAN), which not only solves the problems brought by the convolution structure. The size of the receptive field is limited, which also makes the generation of each local region coordinated with the global details when generating images.

III. METHODS

Although the existing DSC algorithm improves the clustering performance to a certain extent, the receptive field of its network structure is limited, that is, the excessive number of channels makes it difficult for the convolution operation to capture the different local structures of the data, and the learned data is hidden. The feature distribution cannot reconstruct discriminative samples. Therefore, this section proposes a deep subspace clustering algorithm based on the self-attention adversarial mechanism, which introduces a self-attention module into the DSC network and constrains the data feature distribution to approximate any prior probability.

A. *Network Model and Structure*

The deep subspace clustering network framework based on self-attention confrontation is shown in Figure 1. In order to ensure long-distance dependencies in the feature learning process, we add a self-attention module after the last layer of convolutional network in the encoding module. The structure of the self-attention module is shown in Figure 2. The data of the previous layer of network is obtained through a 1×1 convolutional network to obtain K, KQ. Multiply K transpose and V and normalize by 80ftmax to get the attention map, and then dot product with Q to get the final self-attention feature map. In the discriminant network, the number of channels output in the penultimate layer of convolutional network is 1000. Since the number of channels is too large, it will be difficult for the convolution operation to deal with the relationship between different parts, so we also add a self-attention here. force module. When training a generative adversarial network, because the discriminator is too powerful, it is easy to cause the output gradient value to be 0, that is, the gradient disappears, resulting in insufficient gradient information to update the generator. For the gradient vanishing problem of generative adversarial network, many scholars have improved its loss function. Equation (2) The choice of cross-entropy has its limitations whether it is KL-divergence or JS-divergence. We propose WassersteinGAN (WGAN), which uses Earth-mover (EM) distance to measure the distance between the two distributions, and removes the logarithmic log operation, the generation loss and discriminative loss functions are separately expressed as follows:

$$\mathrm{L}_{gen} = -E_{x\sim p_{\mathrm{data}}(x)}[D(x)], \mathrm{L}_{\mathrm{dis}} = \mathrm{E}_{z\sim p(z)}[D(G(z))] - \mathrm{E}_{x\sim p_{\mathrm{data}}(x)}[D(x)] \quad (2)$$

However, each update of the discriminator in the above formula needs to truncate the absolute value of the gradient information, which does not exceed a fixed constant to ensure the stability of the discriminator. Therefore, WGAN-GP (Improved training of Wasserstein GANsP J adds gradient truncation as a gradient penalty term to equation (2), but this needs to satisfy the Lipschitz condition to ensure that the gradient penalty works, and the Lipschitz condition makes the truncated gradient value tend to In order to solve this problem, the concept of Wasserstein divergence for gans (WGAN-div) is proposed to get rid of the dependence of WGAN-GP on Lip8chitz conditional constraints.

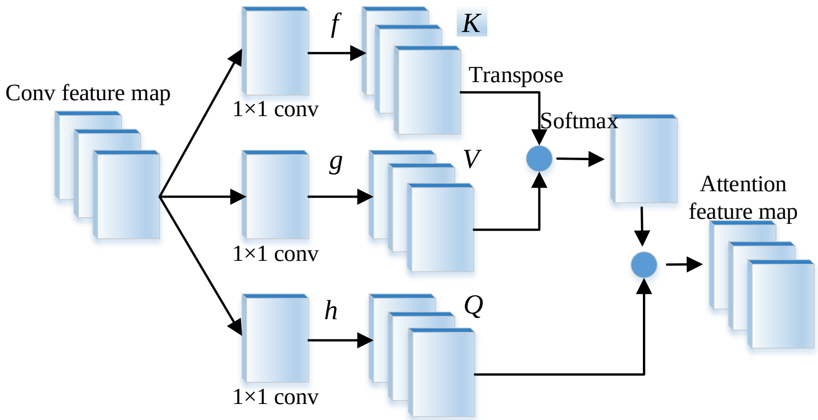

Fig.1 Self-attention module

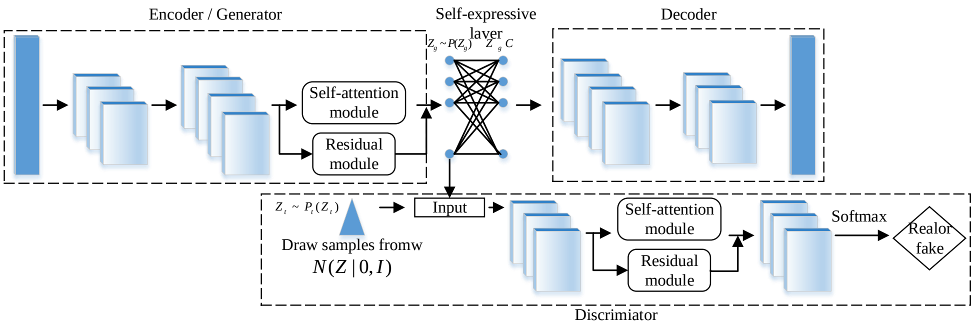

Fig. 2 Framework of deep subspace clustering network based on self-attention confrontation

Synthesizing the GAN and its variants studied by the predecessors, the loss function of the generative adversarial network part of our network is constructed as follows:

$$\mathrm{L}_{gen} = -\mathrm{E}_{Z_g \sim P_g(Z_g)}\left[f_D\left(Z_g\right)\right] \quad (3)$$

$$\mathrm{L}_{\text{dis}} = \mathrm{E}_{Z_g \sim P_g(Z_g)}\left[f_D\left(Z_g\right)\right] - \mathrm{E}_{Z_r \sim P_r(Z_r)}\left[f_D\left(Z_r\right)\right] + \lambda_3 \mathrm{E}_{\hat{Z} \sim P(\hat{Z})}\left[\left\| f_D(\nabla \hat{Z})\right\|^3\right] \quad (4)$$

Among them, in the generative adversarial network structure, the encoding module can be regarded as a generative module for generating feature representations. Therefore, from the perspective of generative adversarial network, B is a fake sample, and the real sample has always been sampled from a prior distribution, which can obey standard Gaussian distribution, mixed Gaussian distribution, etc. The true and false features are input to the discriminator network at the same time, and the feature distribution structure generated by the generator tends to the set prior distribution structure through game training, so that the decoder can generate samples using the self-prior distribution p(z). It becomes the observation data, thereby improving the robustness of feature learning and increasing the anti-interference ability of the network. Due to the introduction of gradient penalty, the discriminator can stably output gradient information to update the generator, thus ensuring the stability of the entire network. Considering the introduction of a generative adversarial network, we rewrite equation (3) as follows:

$$\mathrm{L}_c = \frac{1}{2}\| X - \hat{X}\|_F^2 + \frac{\lambda_1}{2}\left\| Z_g - Z_g C\right\|_F^2 + \lambda_2 \| C\|_F \quad (5)$$

Compared with formula (3), the feature representation in the above formula has been optimized by generative adversarial network and has the structural characteristics of prior distribution. Besides, besides the white attention module, we also add a residual module to deepen the depth of the network. Since the residual module is an internal part of the deep neural network, the loss function of the network remains unchanged. After introducing the residual module, the output of the self-attention module and the output of the residual module are added as the input of the next neural network unit. The residual module is a convolutional network with two convolution kernels of size 3×3, and the convolution stride is 1.

B. Network training

Combining clustering and generative adversarial mechanisms, the overall loss function of the network is:

$$\mathrm{L}_{\text{total}} = \mathrm{L}_c + \mathrm{L}_{\text{gen}} + \mathrm{L}_{\text{dis}} \quad (6)$$

When training a generative adversarial network, the iterative training of the generative loss and the discriminative loss achieves mutual updating. Repeat steps 1 to 3 until the maximum epoch value is reached. The output self-representation coefficient c, once the network training is completed, the adjacent relationship of the data will be learned, and finally C is clustered by spectral clustering to obtain the clustering result of the data.

IV. Experimental results and analysis

This experiment is based on the Python programming language for simulation, the operating system is Ubuntu, the main software architecture is TensorFlow 1.0, CUDA 8.0 and cuDNN 5.1 are configured, and four NVIDIA GPUs GTX 1080Ti are used.

A. Experimental dataset and parameter settings

To verify the effectiveness of the proposed algorithm, we conducted experiments on five public datasets, two handwritten digit datasets MN-IST and USPS, an item dataset COIL-20, and a face dataset Extended Yale B (hereinafter collectively referred to as Yale B) and a clothing dataset Fashion-MNIST hereinafter collectively referred to as FMNIST. The details of the dataset are shown in Table 1. For the 5 datasets, our experimental parameters are shown in Table 2. Among them, input 1 and A2 are the weight parameters of the contribution to the self-representation term and the regularization term, respectively. For the convenience of parameter adjustment, we set input 1=1. In addition, during the experiment, we found that the parameters in Eq. (5) have little influence on the results, which may be because the gradient penalty in the generative adversarial network can make the network stable.

Table 1 Dataset Information

Data set	Category	Quantity	Size
MNIST	10	1000	28×28
FMNIST	10	1000	2828
COIL-20	20	1440	32×32
Yale B	38	2432	48×32
USPS	10	9298	16×16

Table 2 Parameter settings

Data set	λ_1	λ_2	λ_3
MNIST	1	0.5	10
FMNIST	1	0.0001	100
COIL-20	1	30	10
Yale B	1	0.06	24
USPS	1	0.1	10

B. Network Structure Information

In the experiment, the encoder network structure is a three-layer convolutional network. The network structure of the decoder and the encoder is symmetrical. The Fashion-MNIST encoder is a one-layer convolutional network and three residual modules. The decoder is also symmetrical. COIL-20 Only one layer of convolutional network is used, and the specific parameters of the convolutional network are shown in Table 3.

Table 3 Network structure parameters

Data set	Convolution kernel size	Number of channels
MNIST	[5,3,3]	[10,20,30]
FMNIST	[5,3,3,3]	[10,20,30,40]
COIL-20	[3]	[15]
Yale B	[5,3,3]	[64,128,256]
USPS	[5,3,3]	[10,20,30]

In all experiments, the discriminator network adopts three-layer convolutional network, all of which are 1×1 convolution kernels, in order to increase the information exchange of channels, and the number of channels is f1000, 1000, 11. At the same time, we add a self-attention module to the penultimate layer of the discriminator network to increase the long-range dependencies of 1000 channel features. For the pre-training of algorithms, most deep clustering algorithms based on auto-encoders use auto-encoders for pre-training. However, since the algorithm in this paper introduces a generative adversarial network, in order to avoid the initial training of the discriminator being too powerful and interfering with feature learning, we use an adversarial autoencoder (AAE) for pre-training.

C. Evaluation indicators

To evaluate the superiority of our algorithm, we adopt two commonly used metrics: Clustering Accuracy (ACC) and Standard Mutual Information (NMI) as the effect of clustering.

$$ACC\% = \frac{\text{Correct clustering samples}}{\text{Total sample}} \times 100\% \quad (7)$$

$$NMI\% = \frac{2I(A,B)}{H(A)+H(B)} \times 100\% \quad (8)$$

D. Experimental results

In the experiment, this paper adopts the deep clustering method related to the proposed algorithm to compare the experimental results, including: Struct-AEl521, DASC, DCN, DSC and DEC. The experimental results are shown in Table 4. The experimental data are the average of 30 repetitions, and the bold numbers represent the optimal value. Because the authors of Struct AE and DASC do not have open source code, their experimental data are quoted from the original paper. In addition, since it did not conduct experiments on FMNIST and USPS, there is no experimental data comparison on these two datasets. DSC in the dataset Yale B, COIL-20. The experimental results of MNIST refer to his paper, and the experimental results of FMNIST and USPS are obtained by our test. The experimental results of DEC and DCN on Yale B and COIL-20 are tested by us, and the rest are quoted from the original paper. Among them, the experimental results of DEC in Yale B are too unreasonable. We adjusted the network parameters for many times without significant changes. Therefore, DEC has no test results in Yale B, which is represented by "b". It can be seen from Table 4 that our algorithm is in ACC and The NMI index is superior to the other 6 deep clustering algorithms. By comparing the results of DSC-L1, DSC-L2 and our algorithm, it can be seen that the feature representation learned by the self-attention generative adversarial network can achieve better clustering. For example, on the MNIST dataset, our algorithm improves the ACC and NMI of suboptimal DEC by 0.1110 and 0.1281, respectively. The result of DEC on Yale B and the result of DCN on COIL-20 Poor because it has no self-representation structure and does not capture the correlation between data well. DSC, DASC and our algorithm all contain self-representative structures, so they outperform DEC and DCN on some data. To explore the stability of our generative adversarial network, we therefore visualize the training loss for MNIST. In addition, compared with SAADSC, the DSC network has no self-attention module and adversarial network. We chose the results of DSC-L2 for comparison. It can be found that after adding the self-attention module and the adversarial network, the algorithm has better clustering accuracy and standard mutual information. All have improved. In order to explore the influence of different prior distributions on the results, we choose three different distributions to conduct experimental comparisons on three datasets.

Table 4 Experimental results of 5 datasets

Data set	Yale B		COIL-20		MNIST		FMNIST		USPS	
Measurement method	ACC	NMI	ACC	NMI	ACC	NMI	ACC	NMI	ACC	NMI
DSC-L1	0.9666	0.9685	0.9316	0.9393	0.7283	0.7215	0.4768	0.6153	0.6985	0.6767
DSC-L2	0.9735	0.9701	0.9366	0.9405	0.7503	0.7316	0.5816	0.6135	0.7286	0.6965
DEC	*	*	0.6286	0.7788	0.8433	0.8000	0.5903	0.6013	0.7526	0.7406
DCE	0.4303	0.6303	0.1888	0.3036	0.7505	0.7485	0.5866	0.5941	0.7382	0.7692
Struct-AE	0.9722	0.9736	0.9325	0.9563	0.6572	0.6999	-	-	-	-
DASC	0.9855	0.9803	0.9637	0.9585	0.8043	0.7803	-	-	-	-
SAADSC	0.9898	0.9853	0.9752	0.9747	0.9544	0.9283	0.6316	0.6245	0.7853	0.8136

E. Ablation Study

In order to evaluate the role of each module in the proposed network, we test it separately, Test 1 represents the network after removing the self-attention module and residual module: Test 2 is the network with the self-representation layer removed, through the spectral clustering algorithm Cluster the adjacency matrix formed by c = α; Test 3 uses K-means to cluster B after excluding the self-representation layer; Test 4 excludes the residual module in the network. The experimental results are shown in Figure 3 and Table 5. We can see that the residual module contributes the least to the network, and the self-representation layer has the greatest effect, followed by the white attention module. Since the self-representation layer constructs a linear representation between data, the coefficient matrix obtained by the self-representation layer reflects the correlation of intra-class data and the irrelevance of inter-class data.

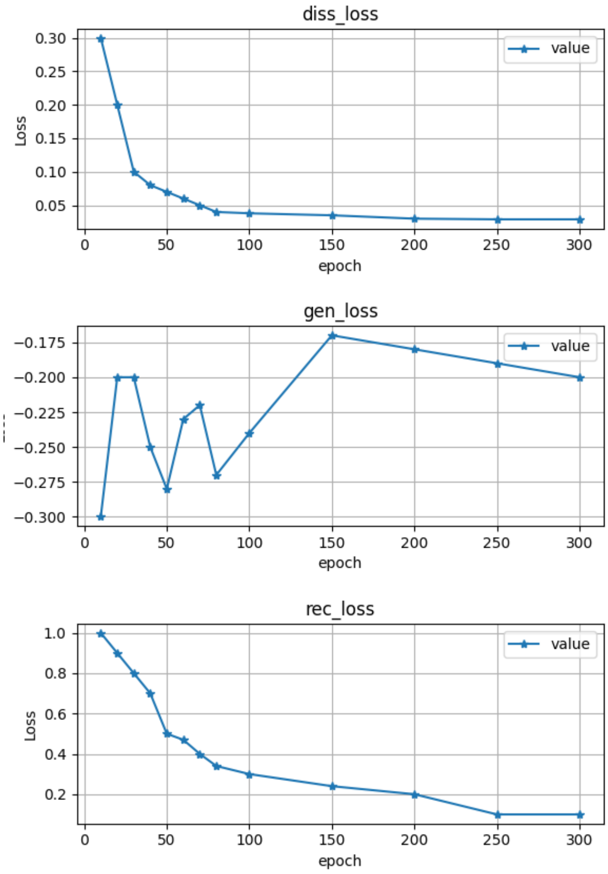

Fig.3 Network training loss for MNIST

Table 5 Experimental results of different prior distributions

Data set	MNIST		FMNIST		USPS	
Measurement method	ACC	NMI	ACC	NMI	ACC	NMI
Gaussian distribution	0.9544	0.9283	0.6217	0.6244	0.7853	0.8136
Bernoulli distribution	0.9323	0.9045	0.6083	0.5992	0.7755	0.7915
Deterministic distribution	0.8672	0.8365	0.5583	0.5792	0.7797	0.7916

F. Robustness experiment

Additionally, to test whether our feature representation is more robust than deep subspace clustering algorithms, we conduct noise tests on the COIL-20 and USPS datasets. Specifically, the corresponding percentage of pixels are replaced with random Gaussian noise, and the algorithms DSC-L1, DSC-L2 and DASC are used for comparison. Because the DASC code is not open source, there is no comparison data in the USPS noise experiment. And because DASC uses histograms for comparison, the experimental data of COIL-20 in Table 6 are approximate estimates of the histograms of their papers. The rest are test results. The experimental results are shown in Table 7 and Table 8. It can be seen that the results of DSC-L1 and DSC-L2 decrease significantly with the increase of noise, while DASC and SAADSC have anti-interference ability due to the introduction of generative adversarial network. Compared with DASC, the self-attention mechanism of our network will play an active role in the generative adversarial learning process, thereby improving the anti-interference ability of the algorithm.

Table 6 The roles of different modules in the SAADSC network

Data set	Yale B		COIL-20		MNIST		FMNIST		USPS	
Measurement method	ACC	NMI	ACC	NMI	ACC	NMI	ACC	NMI	ACC	NMI
Test 1	0.9723	0.9674	0.9384	0.9495	0.8823	0.8606	0.6083	0.6113	0.7747	0.7836
Test 2	0.0712	0.0962	0.4227	0.6265	0.6423	0.5942	0.5383	0.4916	0.6105	0.5513
Test 3	0.0846	0.1225	0.6995	0.7853	0.6613	0.6765	0.6143	0.5924	0.3828	0.3853
Test 4	0.9783	0.9704	0.9685	0.9742	0.9503	0.9277	0.6214	0.6145	0.7853	0.7986
DSC-L2	0.9735	0.9705	0.9366	0.9406	0.7503	0.7316	0.5816	0.6135	0.7286	0.6966
SAADSC	0.9898	0.9855	0.9753	0.9743	0.9542	0.9283	0.6314	0.6243	0.7852	0.8136

Table 7 COIL-20 clustering results with noise

Data set	SAADSC		DSC-L1		DSC-L2		DASC	
Measurement method	ACC	NMI	ACC	NMI	ACC	NMI	ACC	NMI
No noise	0.9752	0.9746	0.9316	0.9356	0.9366	0.9406	0.9636	0.9686
10% noise	0.9593	0.9704	0.8452	0.8977	0.8716	0.9105	0.9023	0.9393
20% noise	0.9113	0.9595	0.8177	0.8738	0.8284	0.8856	0.8604	0.9195
30% noise	0.8706	0.9636	0.7986	0.8572	0.8074	0.8786	0.8355	0.9146
40% noise	0.8566	0.9274	0.6786	0.7858	0.7253	0.8185	0.7807	0.8755

Table 8 USPS clustering results with noise

Data set	SAADSC		DSC-L1		DSC-L2	
Measurement method	ACC	NMI	ACC	NMI	ACC	NMI
No noise	0.7852	0.8136	0.6986	0.676	0.7286	0.6965
10% noise	0.7777	0.7972	0.6706	0.6426	0.6565	0.6626
20% noise	0.7755	0.7903	0.6666	0.6156	0.6533	0.6426
30% noise	0.7717	0.7846	0.6384	0.5988	0.6456	0.6396
40% noise	0.7676	0.7753	0.6045	0.5755	0.6353	0.6161

V. CONCLUSION

For the complexity of family intimacy and adaptability, realistic parenting pressure and co-parenting level, this paper proposes a deep subspace clustering based on adversarial training, which uses the game learning ability of the adversarial network to make the feature representation learned by the encoder network obey the preset prior distribution characteristics. Deep subspace clustering based on self-attention adversarial to enhance the robustness of feature learning, thereby improving the clustering performance. The experimental results show that the proposed algorithm outperforms the state-of-the-art methods in terms of ACC and NMI. We believe that family intimacy can be well modeled based on self-attention and give suggestions that are more conducive to family harmony.

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REFERENCES

[1] Kim, S. B. . (2021). The mediating effects of child-bearing attitude of the relationship between parenting stress and depression of the mothers with adhd child. *JOURNAL OF SPECIAL EDUCATION & REHABILITATION SCIENCE, 60*(2), 133-146.

[2] Cejas, I. , Mitchell, C. M. , Barker, D. H. , Sarangoulis, C. , Eisenberg, L. S. , & Quittner, A. L. . (2021). Parenting stress, self-efficacy, and involvement: effects on spoken language ability three years after cochlear implantation. Otology & Neurotology, 42(10S), S11-S18.

[3] Wakimizu, R. , & Wang, T. . (2022). Parenting stress of chinese mothers living and child-rearing in japan and related factors. Journal of Nursing (English), 12 (2), 18.

[4] Schuler, B. R. , Daundasekara, S. S. , Hernandez, D. C. , Dumenci, L. , & Miller, A. L. . (2020). Economic hardship and child intake of foods high in saturated fats and added sugars: the mediating role of parenting stress among high-risk families. Public Health Nutrition, 23(15), 1-12.

[5] Cho, Y. I. , Kim, H. J. , & Dong, H. K. . (2021). The mediating effects of parenting stress on the relationship between the health problems of children with food allergies and the perceived health status of parents. Korean Journal of Stress Research, 29(2), 115-121.

[6] Gao, X. , & Lee, K. . (2021). Factorial structure and cross-cultural invariance of the parenting stress index-short form in hong kong and thailand. Frontiers in psychology, 12, 661972.

[7] Schreiber, J. , Cole, J. , Houtrow, A. , Kallan, M. , Thom, E. , & Howell, L. , et al. (2021). Maternal depressive risk in prenatal versus postnatal surgical closure of myelomeningocele: associations with parenting stress and child outcomes. Fetal diagnosis and therapy, 48(6), 479-484.

[8] Brisini, K. , & Solomon, D. H. . (2021). Distinguishing relational turbulence, marital satisfaction, and parenting stress as predictors of ineffective arguing among parents of children with autism:. Journal of Social and Personal Relationships, 38(1), 65-83.

[9] Savenysheva, S. S. , & Zapletina, O. O. . (2021). Social support as a factor of parenting stress for mothers of young and preschool children. Vestnik Kostroma State University Series Pedagogy Psychology Sociokinetics, 27(1), 126-132.

[10] Haque, M. A. , Salwa, M. , Sultana, S. , Tasnim, A. , Towhid, M. , & Karim, M. R. , et al. (2022). Parenting stress among caregivers of children with neurodevelopmental disorders: a cross-sectional study in bangladesh:. Journal of Intellectual Disabilities, 26(2), 407-419.

[11] Ji, Y. L. , & Lee, K. . (2021). Effects of parenting stress on preschoolers' emotion regulation: mediating role of parent's responses to children's negative emotions. Korean Journal of Child Studies, 42(1), 119-134.

[12] Xue Fei Zhao (2020). Research on the relationship among family intimacy, school adaptation and mental health. Advances in Social Sciences, 09(1), 41-47.

[13] Awk, A. , Tra, A. , At, B. , Kmga, C. , Jm, D. , & Nzm, E. , et al. (2020). Exploring parenting contexts of latinx 2-to-5-year old children's sleep: qualitative evidence informing intervention development. Journal of Pediatric Nursing, 54, 93-100.

[14] Wiley, B. , Ghanim, F. , Taylor, K. , & Murias, K. . (2021). P.124 baseline assessment of attention and executive function deficits in children with neurodevelopmental disorders: data from a speciality attention clinic. Canadian Journal of Neurological Sciences / Journal Canadien des Sciences Neurologiques, 48(s3), S54-S55.

[15] Wolf, J. P. , Freisthler, B. , & Chadwick, C. . (2021). Stress, alcohol use, and punitive parenting during the covid-19 pandemic. Child Abuse & Neglect, 117(5), 105090.

[16] Pratiwi, H. , Yarliani, I. , Ismail, M. , Haida, R. N. , & Asmayanti, N. . (2020). Assessing the toxic levels in parenting behavior and coping strategies implemented during the covid-19 pandemic. JPUD - Jurnal Pendidikan Usia Dini, 14(2), 231-246.

[17] Shin, E. , Choi, K. , Resor, J. , & Smith, C. L. . (2021). Why do parents use screen media with toddlers? the role of child temperament and parenting stress in early screen use. Infant Behavior and Development, 64(5), 101595.

[18] Cy, A. , & Ls, B. . (2021). Coping self-efficacy and parenting stress in mothers of children with congenital heart disease. Heart & Lung, 50(2), 352-356.

[19] Amaerjiang, N. , Amaerjiang, N. , Amaerjiang, N. , Xiao, H. , Xiao, H. , & Xiao, H. , et al. (2021). Sleep disturbances in children newly enrolled in elementary school are associated with parenting stress in china. Sleep Medicine, 88, 247-255.

[20] Ren, X., Ahmed, I., & Liu, R. Study of Topological Behavior of Some Computer Related Graphs. Journal of Combinatorial Mathematics and Combinatorial Computing, 117, 3-14.

[21] Nazeer, S., Sultana, N., & Bonyah, E. Cycles and Paths Related Vertex-Equitable Graphs. Journal of Combinatorial Mathematics and Combinatorial Computing, 117, 15-24.