Efficient Deep Embedded Subspace Clustering
Supplementary Materials

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1. Explanation for the parameters in Table 1 of Section 2.3

Here we provide a detailed explanation for the parameters in Table 1 of Section 2.3. of the main paper. Specifically, $n_s, m < n$, $0 < \rho \leq 1$ denotes the proportion of nonzero elements, and k denotes the number of clusters. l and p denote the dimensions of the feature generated by the deep encoder in each of the deep clustering methods. $\tilde{m} = \max\{m, h_{max}\}$, where h_{max} denotes the size of the widest hidden layer in each of the neural networks. $\tilde{l}$ denotes the size of the hidden layer next to the largest hidden layer. θ denotes the number of parameters in a deep learning model. Amongst the deep subspace clustering method, our method has linear time and space complexities in terms of n, while other methods have quadratic time and space complexities.

2. Details of the online clustering

Tab. 1 provide more details about the Human Activities Recognition (HAR) [1] dataset used Section 4.8 of the main paper.

Dataset name	# Total samples	# Classes	# Size
HAR	10,299	6	561

Table 1. Detailed information of the HAR dataset.

We also illustrate the experimental settings of Section 4.8 here. Note that the three algorithms used for comparison follow the same experimental setup. The procedures are summarized into Algorithm 1. Specifically, we first pre-train 1,000 randomly selected samples from the dataset, and the number of pre-train epochs are set to 20. After the pre-train is completed, the model is initialized with the pre-trained weights. In the subsequent training round, we set $b = 30$ to randomly select completely new samples to simulate online clustering, the embedding dimension p and subspace dimension d are set to 30 and 3, respectively. The hyper-parameters follow the settings in the paper, the training epochs per round T_E is set to 10, and the network is trained iteratively in this way. It should also be noted that the newly added samples are trained together with those samples from the previous round.

The clustering performance on STL-10 and REUTERS-10K shown in the paper verified the feasibility and effectiveness of our method in online clustering.

3. Further comparison with some SOTA subspace clustering methods in USPS

We also conduct experiment on USPS dataset and further compared with some SOTA subspace clustering approaches including Double Low-Rank Representation with Projection Distance penalty (DLRRPD) [1] and Deep Spectral Clustering using Dual Autoencoder Network (DSCDAN) [2] to demonstrate the effectiveness of the proposed DSSEC method. The detailed information of USPS dataset is described in Tab. 3.

Dataset name	# Total samples	# Classes	# Size
USPS	9,298	10	256

Table 3. Detailed information of the USPS dataset.

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[1]https://archive.ics.uci.edu/ml/datasets/Human+Activity+Recognition+Using+Smartphones

Methods		DSC-Net	k-SCN	DLLRPD [1]	DSCDAN [2]	EDESC
Time Complexity		$O(ln^2)$	$O(ln^2)$	$O(n^3)$	$O(ln^2)$	$O(\tilde{d}pn)$
MNIST	ACC	0.532	**0.833**	0.682	0.818	**0.913**
	NMI	0.479	0.773	0.661	**0.872**	**0.862**
USPS	ACC	0.689	**0.875**	0.599	0.806	**0.911**
	NMI	0.735	0.797	0.555	**0.850**	**0.831**

Table 2. Newly added baselines on MNIST (to save place here) and newly added USPS dataset. Note that $\tilde{d} < l, p \ll n$.

Algorithm 1 Online clustering algorithm of the proposed method

Input: Initial input data $\mathbf{X}_0$, randomly partitioned data $\mathbf{X}_1, \mathbf{X}_2, \cdots, \mathbf{X}_i \in \mathbb{R}^{m \times b}$, embedding dimension p, subspace dimension d, number of clusters k, hyper-parameters η and β, training epochs per round T_E.
Output: Cluster labels $\mathcal{C}$.

Pre-train with original data $\mathbf{X}_0$.
Initialize the network with the pre-trained model.
Initialize the subspace bases proxy $\mathbf{D}$ with k-means clustering.
for $i = 1, 2, \cdots$ **do**
    if $i = 1$ **then**
        Concatenate $\mathbf{X}_0$ with $\mathbf{X}_1$ to form new data $\mathbf{X}_{New}$
    else
        Concatenate $\mathbf{X}_{New}$ with $\mathbf{X}_i$
    end if
    for $j = 1$ to T_E **do**
        Learn embedded representation $\mathbf{Z}$ from $\mathbf{X}_{New}$.
        Compute the subspace affinity S
        Compute the refined subspace affinity $\widetilde{S}$.
        Compute the loss terms L_{Recon} and L_{Sub}.
        Compute the regularization term D_{Cons}.
        Update network parameters and subspace bases proxy $\mathbf{D}$ by minimizing the objective function.
    end for
end for
Obtain the final updated cluster labels from S.
return Cluster labels $\mathcal{C}$.

References

[1] Zhiqiang Fu, Yao Zhao, Dongxia Chang, Xingxing Zhang, and Yiming Wang. Double low-rank representation with projection distance penalty for clustering. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 5320–5329, 2021. 1, 2

[2] Xu Yang, Cheng Deng, Feng Zheng, Junchi Yan, and Wei Liu. Deep spectral clustering using dual autoencoder network. In *Proceedings of the IEEE/CVF cConference on Computer Vision and Pattern Recognition*, pages 4066–4075, 2019. 1, 2