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# Supplementary Material for Learning from Disjoint Views: A Contrastive Prototype Matching Network for Fully Incomplete Multi-View Clustering

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## 1 Introduction

In this supplementary material, we provide a detailed description of the network architecture for our model (CPMN) and present additional experiments to further validate its effectiveness. Furthermore, the source code has been submitted.

## 2 Network Architecture

Table 1: The architecture of the view-specific autoencoders in CP MN

Encoder	Decoder
Dense(ReLU, size = $\frac{1}{2}d_v$ )	Dense(ReLU, size = $d_z$ )
Dense(ReLU, size = $\frac{1}{2}d_v$ )	Dense(ReLU, size = 1000)
Dense(ReLU, size = 1000)	Dense(ReLU, size = $\frac{1}{2}d_v$ )
Dense(size = $d_z$ )	Dense(ReLU, size = $d_v$ )

The model of CP MN consists of a set of view-specific autoencoders and cluster layers. As can be seen from Table 1, the view-specific encoders and decoders are stacked by fully connected layers with the size of  $[\frac{1}{2}d_v, \frac{1}{2}d_v, 1000, d_z]$  and  $[1000, 1000, \frac{1}{2}d_v, d_v]$ , where  $d_v$  and  $d_z$  denote the original feature dimension and the latent feature dimension for the  $v$ -th view, respectively. Additionally, the cluster layers are also fully connected layers containing  $C$  neurons, where  $C$  is the number of clusters of each dataset.

## 3 Additional Experiments

In this section, we carry out additional experiments including parameter sensitivity analysis and convergence analysis to further show the effectiveness of the proposed CP MN.

### 3.1 Parameter sensitivity analysis of MNN

Our proposed model employs a correspondence-free graph contrastive learning strategy predicated on mutual  $k$ -nearest neighbors (MNN) to uncover structural correlations. This approach generates pseudo-alignments via feature affinity, thereby obviating the need for pre-existing correspondences.

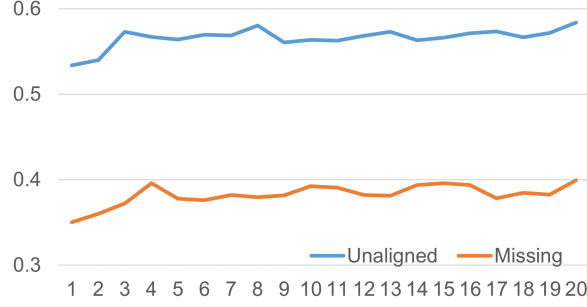


Figure 1: ACC vs.  $k$  with fully incomplete multi-view data

The number of nearest neighbors,  $k$ , is a well-recognized critical parameter in graph-based learning methods, often exerting a substantial impact on clustering performance. To examine the influence of  $k$  on our CPMN, a sensitivity analysis is conducted on the Caltech-101 dataset. As can be seen from the figure 1, our model is insensitive to  $k$  in the range of  $k \in [3, 20]$ , achieving satisfactory performance within this interval. When  $k$  is less than 3, clustering performance gradually improves as  $k$  increases. This suggests that an overly small  $k$  provides insufficient structural information for reference.

### 3.2 Convergence analysis with the number of MNN

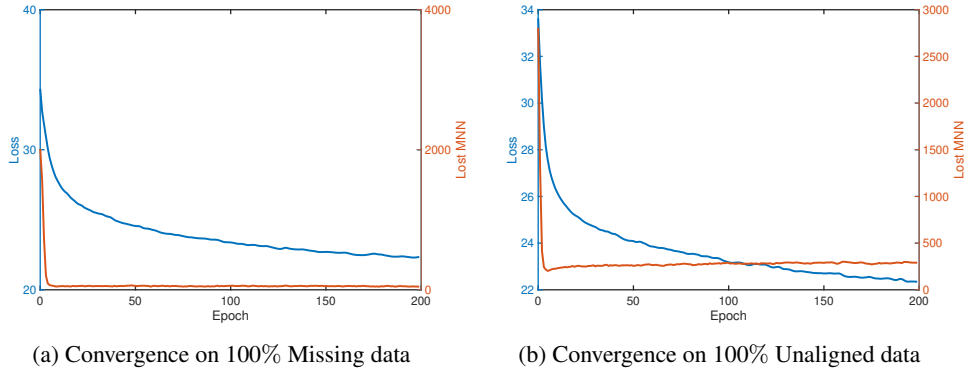


Figure 2: Convergence on the Caltech-01 dataset. The left and right y-axis denote the loss value and the number of samples where MNN is not detected, respectively.

Methods utilizing mutual  $k$ -nearest neighbors (MNN) are generally more robust than  $k$ NN-based approaches, though MNNs may not always be found for every sample. To visualize the number of samples where MNN is not detected during the CPMN training process, we investigate its convergence by reporting the loss value and the count of samples with undetected MNNs as training progresses. Experiments are run on Caltech-101 with  $k = 5$  under both defined incompleteness scenarios. As depicted in the figure 2, the loss value decreases sharply in the first 10 epochs before converging gradually. Regarding the number of samples with undetected MNNs, this count drops sharply within the first two epochs and subsequently remains at a low level throughout the training. Although samples with undetected MNNs persist, they constitute a very small proportion of the total dataset.

## 4 Source Code

The source code for the CPMN presented in this paper can be found in the “CPMN\_code.zip” file. This compressed package includes the source code for both fully missing and fully unaligned data scenarios. Due to supplementary material space limitations, the datasets are not included within this archive but can be downloaded from the following anonymous link: [https://drive.google.com/file/d/1HGKDCyBXkjCBrkJlYsWUFFVREm6\\_E8zc/view](https://drive.google.com/file/d/1HGKDCyBXkjCBrkJlYsWUFFVREm6_E8zc/view).