MCGNet: Partial Multi-view Few-shot Learning via Meta-alignment and Context Gated-aggregation

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Abstract

In this paper, we propose a new challenging task named as \textit{partial multi-view few-shot learning}, which unifies two tasks, i.e. few-shot learning and partial multi-view learning, together. Different from the traditional few-shot learning, this task aims to solve the few-shot learning problem given the incomplete multi-view prior knowledge, which conforms more with the real-world applications. However, this brings about two difficulties within this task. First, the gaps among different views can be large and hard to reduce, especially with sample scarcity. Second, due to the incomplete view information, few-shot learning becomes more challenging than the traditional one. To deal with the above issues, we propose a new \textit{Meta-alignment and Context Gated-aggregation Network} by equipping meta-alignment and context gated-aggregation with partial multi-view GNNs. Specifically, the meta-alignment effectively maps the features from different views into a more compact latent space, thereby reducing the view gaps. Moreover, the context gated-aggregation alleviates the view-missing influence by leveraging the cross-view context. Extensive experiments are conducted on the PIE and ORL dataset for evaluating our proposed method. By comparing with other few-shot learning methods, our method obtains the state-of-the-art performance especially with heavily-missing views.

1 Introduction

Deep learning methods based on the large scale datasets have shown remarkable superiority in many computer vision tasks, such as image segmentation [Banerjee \textit{et al.}, 2019; Zhang \textit{et al.}, 2019b], object detection [Pan \textit{et al.}, 2019; Hu \textit{et al.}, 2018]. However, for some applications, e.g. disease diagnosis [Prabhu, 2019] and drug discovery [Altae-Tran \textit{et al.}, 2017], it is expensive or even impossible to obtain sufficient training data due to privacy and ethical issues. Therefore, large efforts have recently been paid on the few-shot learning [Sung \textit{et al.}, 2018; Ramalho and Garnelo, 2019; He \textit{et al.}, 2020] which concentrates on well training the deep-learning models from few training samples. These works devoted only to solving the classification problem with single view. Thus, they cannot well handle real-world problems, where data can often be acquired with incomplete multiple views. Therefore, multi-view learning with partially missing views, named as partial multi-view learning [Zhang \textit{et al.}, 2019a] emerges. This motivates us to propose a new task named as \textit{partial multi-view few-shot learning}, which aims to solve the few-shot learning problem under the circumstance of partially missing views. As shown in Figure 1, this task realizes the category prediction for the samples from unobserved classes, based on the incomplete multi-view prior knowledge of support samples. Obviously, this task is one step closer to the real-world applications of the deep-learning frameworks. However, it is also more challenging than the traditional few-shot learning in the following two aspects. First, large view gaps generally exist in the multi-view data. Since the query and support samples are from the unobserved classes and with limited number, our task is much difficult in reducing cross-view gaps. Second, the incomplete view information results in the inconsistency of the feature representation, thereby severely limiting the inference accuracy.

To address the above-mentioned difficulties, we propose a new \textit{Meta-alignment and Context Gated-aggregation Network} (MCGNet), as illustrated in Figure 2. Our MCGNet is comprised of three key components, i.e. Partial Multi-view GNNs (PMGNNs), Meta-alignment Module (MM) and...
Context Gated-aggregation Module (CGM). First, PMGNNs preliminarily model the relation between the query-support sample pairs for each individual view by utilizing the incomplete intra-view information. Then, the features of PMGNNs from different views are further manipulated by the proposed MM and CGM. Specifically, MM effectively meta-aligns the features of different views into a more compact latent space which reduces the cross-view gaps, while maintaining high generalization on unobserved categories. In addition, CGM aims to conquer the view-missing difficulty by appropriately aggregating the cross-view context. Overall, MCGNet is feasible to generate an improved feature representation, as well as complete the missing views by using the information from other existing views. To validate the effectiveness of our MCGNet, extensive experiments are conducted on the two public datasets PIE and ORL which are released in [Zhang et al., 2019a]. By comparing with other typical few-shot learning methods, we conclude that our MCGNet obtains the state-of-the-art performance even in the situation of heavily-missing views. The contributions of this paper are summarized as below:

- We present a new challenging task named as **partial multi-view few-shot learning**, which extends the few-shot learning into the scenario of multiple views and missing views;

- To address the defined task, we propose the Meta-alignment and Context Gated-aggregation Network (MCGNet) by integrating meta-alignment and context gated-aggregation with the partial multi-view GNNs. MCGNet can effectively reduce the cross-view gaps, as well as relieve the view-missing issue;

- Extensive experiments demonstrate that our MCGNet achieves the state-of-the-art performance on the proposed task, especially when the view information is heavily missing.

2 Related Work

In this section, we briefly review the recent works on the few-shot learning and partial multi-view learning, which are closely related to our research.

2.1 Few-shot Learning

Few-shot learning targets to learn novel visual concepts from few labelled examples. Typical works for few-shot learning, such as MatchNet [Vinyals et al., 2016] and ProtoNet [Snell et al., 2017], mainly compute the similarity between the query-support sample pairs in the embedding domain. RelationNet [Sung et al., 2018] further extends these works by utilizing CNNs for calculating the relation score. In addition, GCP [Li et al., 2019] further exploits the global context information in the dataset. Inspired by Neural Turing Machines [Graves et al., 2014], [Santoro et al., 2016] proposes MANN that learns the storage of the critical information with the help of the external memory module. Then, [Ramalho and Garnelo, 2019] extends MANN to memorize the most unexpected information, thereby reducing the redundancy and improving feature representation. Moreover, [Douze et al., 2018; Wu et al., 2018; Gao et al., 2018; Kwitt et al., 2016] address the few-shot learning problem by augmenting the training set.

**Discussion.** Currently, the few-shot learning methods are only designed to the unimodal datasets (e.g. image). But, in real-world scenarios, data can often be acquired by multiple views and incomplete views. Based on this observation, we propose the new task as partial multi-view few-shot learning. It extends the traditional few-shot learning into inferring query samples by utilizing the incomplete multi-view prior knowledge of support samples. In order to solve the problem, we further study the partial multi-view learning methods.

2.2 Partial Multi-view Learning

Partial multi-view learning aims to solve the learning problem based on the incomplete multi-view dataset. A straightforward solution is completing the data by missing data imputation and then turning to the full multi-view learning problem. For example, [Tran et al., 2017] proposes the cascaded residual auto-encoder that imputes the missing data by leveraging cross-view relatedness. [Shang et al., 2017] proposes VIGAN by utilizing the Generative Adversarial Networks. In addition, alternative methods are proposed without imputing the missing views explicitly. For example, [Yang et al., 2018] and [Xue et al., 2019] focus on exploiting the information of the relevant unlabelled data in a semi-supervised learning manner. Recently, [Zhang et al., 2019a] proposes CPM-Nets for mapping the multi-view samples into a common embedding space, in which the samples are well clustered.

**Discussion.** We state that the current partial multi-view learning methods are not suitable for the few-shot scenarios directly. Just as indicated in [Tran et al., 2017] and [Shang et al., 2017], sufficient training data are required for training neural networks and data imputing. Therefore, the latent space clustering used in the current partial multi-view learning methods may be failed in the few-shot scenarios. As for the semi-supervised methods, such as [Yang et al., 2018] and [Xue et al., 2019], sufficient unlabelled training data are required excessively. Last but not the least, the current partial multi-view learning methods cannot deal with the few-shot learning problem with unseen categories. Consequently, our MCGNet are proposed to solve the above issues.

3 Methodology

In this section, we first define the partial multi-view few-shot learning task. Then, we introduce the details of the MCGNet model.

3.1 Partial Multi-view Few-shot Learning

As shown in Figure 1, the partial multi-view few-shot learning aims at inferring the categories of the query samples, by learning from the labelled support samples with incomplete multi-views. Generally, suppose we have a small support set $O_s = \{S_n, y_n\}_{n=1}^{N_s}$ that contains $N_s$ sample-label pairs from $C$ unseen categories. Each sample is composed of incomplete multi-views, i.e. $S_n = \{s_n^v * \mu_n^v\}_{v=1}^{V}$, where $s_n^v$ represents the $v$-th view observation of $S_n$, and $\mu_n^v$ is the existence indicator of view $s_n^v$ (i.e. $\mu_n^v = 1$, if $s_n^v$ is observed and $\mu_n^v = 0$, otherwise).
if otherwise). Then, given a query sample $Q_n$ from the query set $\mathcal{O}_q = \{Q_n\}_{n=1}^{N_q}$, its category $y_n$ can be predicted by leveraging the incomplete multi-view prior knowledge contained in $\mathcal{O}_s$ as Eq.1,

$$y_n = \arg \max_{\tilde{y}_n \in \{1, \ldots, c\}} P(\tilde{y}_n | Q_n, \mathcal{O}_s) \tag{1}$$

where $P(\tilde{y}_n | Q_n, \mathcal{O}_s)$ represents the probability that $Q_n$ is classified as the label $\tilde{y}_n$, conditioned on $\mathcal{O}_s$. Being consistent with the conventional few-shot learning, each episode in our task contains two parts, i.e. $\mathcal{O}_s$ and $\mathcal{O}_q$. In each episode, for each one of the $C$ classes, there are $K$ samples under $V$ partially-available views. Therefore, the task is abbreviated as “C-way K-shot V-view”.

**View-missing rate.** To simulate the deficiencies of views as in real-world applications, we define the view-missing rate $\gamma$ at the mini-batch level as below,

$$\gamma = \frac{\sum_{v=1}^{V} M^v}{N_b \times V} \tag{2}$$

where $N_b$ is the number of support samples in the mini-batch, and $M^v$ represents the number of samples with missing the $v$-th view. In particular, each support sample has one available view observation at least. After that, the view-missing rate of the whole mini-batch can be fixed as the pre-defined value of $\gamma$. Of note, the view-missing rate for each individual episode can still be different, which makes the missing views more diverse.

### 3.2 Meta-alignment and Context Gated-aggregation Network

In Figure 2, we present the overview of Meta-alignment and Context Gated-aggregation Network (MCGNet) for solving partial multi-view few-shot learning. There are three key components in MCGNet, i.e. Partial Multi-view GNNs (PMGNNs), Meta-alignment Module (MM) and Context Gated-aggregation Module (CGM). First, PMGNNs preliminarily models the relation between the query-support sample pairs in each individual view with the usage of incomplete intra-view information. To further reduce the cross-view gaps and alleviate the view-missing effect, MM and CGM are utilized. Finally, the class relation scores for the query samples are calculated and their categories are predicted. The details of each component are presented as below.

**Partial Multi-view GNNs**

For the “V-view” learning task, $V$ GNNs $\{G^v\}_{v=1}^{V}$ are constructed where $G^v = (H^v, A^v)$. Here, $H^v$ is the node features, and $A^v$ is the adjacency matrix that indicates the node edges. For each graph $G^t$, the node features are initialized as $H^v_0$, where the observations and their one-hot labels are concatenated for the support samples, and the observations and zero vectors are concatenated for the query samples, aiming to maintain the same dimension.

After obtaining $H^v_0$, $G^v$ is constructed by repeating two steps, i.e. 1) updating adjacency matrix and 2) updating node features. The adjacency matrix $A^v_i$ in the $t$-th iteration is updated based on the node features $H^v_{t-1}$ in the $(t-1)$-th iteration as shown in Eq.3,

$$A^v_{(i,j), t} = \text{MLP}(|h^v_{i, t-1}; h^v_{j, t-1}|_2; \theta_1) \tag{3}$$

where $h^v_{i, t-1}$ and $h^v_{j, t-1}$ represent the $i$-th and $j$-th node of $H^v_{t-1}$, and $A^v_{(i,j), t}$ represents the $(i, j)$ element of $A^v_i$, i.e. the link between $i$-th and $j$-th node in $H^v_{t-1}$. MLP$(\cdot; \theta_1)$ indicates the Multi-layer Perceptron.

After obtaining $A^v_i$, we further use $A^v_i$ to update the node features $H^v_{t-1}$ by aggregating the relevant incomplete intra-view information and obtain $H^v_t$ as in Eq.4,

$$H^v_t = \text{Gconv}(A^v_i H^v_{t-1}; \theta_2) \tag{4}$$

where $\text{Gconv}(\cdot; \theta_2)$ indicates the graph convolutional layer.

By repeating Eq.3 and Eq.4, $G^v_t$ is evolved in which the nodes with the same class share higher similarity. Therefore, PMGNNs can largely exploit the incomplete intra-view information. To deal with the issues of cross-view gaps and view missing, MM and CGM are further employed.

**Meta-alignment Module**

Since our task focuses on the recognition of unobserved classes given just few labelled support samples, this imposes

\[ \text{Objective function} \xrightarrow{\text{Forward-propagation}} \text{Network joint optimization} \]
The nodes from other views (i.e., \( \delta_{i,j}^{v,k} \)) are selected if \( \delta_{i,j}^{v,k} \) is higher than the pre-defined threshold \( \tau \). Otherwise, the node \( h_j^k \) would be regarded as irrelevant information and filtered. The selected nodes are further weighted by the gated-weights as in Eq. 9. Here, \( \delta_{i,j}^{v,k} \) is computed as 1 \( \times \) 1 convolution \( \text{Conv}(:, \cdot; \theta_3) \) of the cosine similarity between \( h_i^v \) and \( h_j^k \).

After aggregating the cross-view context, the node features of PMGNNs \( \{ \hat{H}_v^v \}_{v=1}^M \) are successively updated and become more informative for all views.

### 3.3 Class Relation Score

Based on the above two subsections, \( \hat{H} = \{ \hat{H}_v^v \}_{v=1}^M \) and \( H = \{ H_v^v \}_{v=1}^M \) are produced. For the \( j \)-th query sample, its class relation scores \( \hat{r}_j \) and \( r_j \) can be calculated by utilizing \( \hat{H} \) and \( H \) as in Eq.10 and Eq.11, respectively.

\[
\hat{r}_j = \text{SM}( \sum_{v=1}^V \sum_{n=1}^N \hat{q}_{j,v}^v \cdot \hat{s}_n^v \cdot \mu_n^v \cdot \text{one}_\text{hot}(y_n) ) \tag{10}
\]

\[
r_j = \text{SM}( \sum_{v=1}^V \sum_{n=1}^N q_{j,v}^v \cdot \bar{s}_n^v \cdot \mu_n^v \cdot \text{one}_\text{hot}(y_n) ) \tag{11}
\]

where \( \hat{q}_{j,v}^v \in \hat{H}_v^v \) and \( q_{j,v}^v \in H_v^v \) indicate the \( v \)-th view features of the \( i \)-th support sample, respectively. Accordingly, \( \hat{s}_n^v \in \hat{H}_v^v \) and \( \bar{s}_n^v \in H_v^v \) denote the \( v \)-th view features of the \( j \)-th query sample, respectively. \( \text{SM}(\cdot) \) is defined as the SoftMax layer.

Defining \( r_j = \frac{\hat{r}_j + r_j}{2} \), the category of the \( j \)-th query sample can be estimated as \( y_j = \arg\max_c r_j[c] \), where \( r_j[c] \) represents the \( c \)-th element of the vector \( r_j \).

### 3.4 Objective Function

Overall, the complete objective function \( \mathcal{L}_{\text{total}} \) of MCGNet is defined by adding \( \mathcal{L}_{\text{cr}} \) and \( \mathcal{L}_{\text{ma}} \), as shown in Eq.13.

\[
\min_\theta \mathcal{L}_{\text{total}} = \min_\theta ( \mathcal{L}_{\text{cr}} + \lambda \mathcal{L}_{\text{ma}} ) \tag{13}
\]

where \( \lambda \) is the hyperparameter that controls the balance between \( \mathcal{L}_{\text{cr}} \) and \( \mathcal{L}_{\text{ma}} \). \( \theta = \{ \theta_i \}_{i=1}^4 \) represents the network parameters to be optimized.

### 4 Experiment

In this section, we first briefly introduce the datasets and the implement details. Then, the evaluation of the proposed MCGNet is conducted by comparing it with the typically related works.
Nets in two aspects. First, CPM adopts for both training and testing.

Moreover, the training and testing mechanism is set as 0, and the hyperparameter is set as 0.9. For all experiments, the threshold \( \eta \) and the initial learning rate \( \eta \) are all based on mini-batch, of which the batch sizes are both 20, intensity, local binary pattern (LBP) and Gabor.

Implement details. All our experiments are executed with Pytorch on a GeForce GTX 1080 Ti Nvidia GPU. The Adam optimizer [Kingma and Ba, 2014] is adopted for training the models with the weight decay set to \( 1e^{-5} \) and the initial learning rate set to \( 2e^{-2} \). In particular, the learning rate decays in the “poly” manner, i.e. \( lr \times (1 - \frac{iter}{iter_{total}})^{power} \), where \( power \) is set as 0.9. For all experiments, the threshold \( \tau \) in the gate mechanism is set as 0, and the hyperparameter \( \lambda \) in the objective function is set as 0.2. Moreover, the training and testing are all based on mini-batch, of which the batch sizes are both set as 20 (i.e. each mini-batch contains 20 episodes). The accuracy is obtained based on 5-fold cross validation. For each fold, 80 % categories are used for training while the remaining unseen 20 % categories are used for testing.

4.1 Dataset and Implement Details

Dataset. We validate all the methods on two public datasets PIE and ORL, provided by [Zhang et al., 2019a]. PIE dataset contains 680 facial images of 68 different people, and ORL dataset contains 400 images of 40 different people. For both PIE and ORL datasets, the features of three different views are extracted, i.e. intensity, local binary pattern (LBP) and Gabor.

4.2 Comparison Results

To validate our method, on one hand, we compare our method with several typical few-shot learning methods such as MatchNet, ProtoNet and RelationNet, which validates the superior of our method in solving the proposed task than the conventional few-shot learning methods. Of note, since the conventional few-shot learning methods cannot naturally handle the multiple views, we have to fuse the results of each view for generating the final predictions. On the other hand, we compare our method with the recent partial multi-view learning method CPM_Nets.

In Figure 3, we compare our MCGNet with the typical few-shot learning methods under different view-missing rates. It can be seen that our MCGNet achieves consistently better performance than other comparison methods on both PIE and ORL datasets. For example, on the “5-way 1-shot 3-view” task, although all the methods show decreased performance when the view-missing rate is increasing, our MCGNet demonstrates the highest robustness to different view-missing rates and achieves the best performance. The same conclusion can be drawn with increasing shot number. These results demonstrate that, by properly reducing the cross-view gaps and exploring the cross-view context, our MCGNet can well handle the heavily-missing view issues, while the typical few-shot learning methods cannot be directly used to tackle our proposed task.

In Table 1, we compare our MCGNet with the typical multi-view learning method CPM_Nets. Our MCGNet is different from CPM_Nets in two aspects. First, CPM_Nets is not performed in the few-shot learning manner. Instead, it is trained on sufficient training data, and tested with the same classes as the training set. However, our MCGNet is
Nets on both datasets. In this way, the effective-
Nets is trained in a transductive way
Furthermore, we also investigate the performance of MCGNet
and each degraded version, we conclude the effectiveness of
information from incomplete multiple views. Furthermore, we
implemented three degraded versions of MCGNet where CGM
and MM are removed respectively and both removed from
MCGNet. Based on the performance gain between MCGNet
and each degraded version, we conclude the effectiveness of
both CGM and MM components. To further prove the signif-
ance of MM, we also provide t-SNE visualization [Maaten
Hinton, 2008] in Figure 5 for comparing the node distri-
Figure 5: The exemplified t-SNE visualization for the node features with/without being processed by our meta-alignment when testing on the
unobserved categories.

4.3 Ablation Study
The ablation study for our method is summarized in Fig-
ure 4, where the performance of each single view and each
degraded version of MCGNet is investigated. In this fig-
ure, we can see that the performance of single view data is
severely deteriorated with a higher view-missing rate. This
indicates the worth of our study on fully exploiting the in-
formation from incomplete multiple views. Furthermore, we
implement three degraded versions of MCGNet where CGM
and MM are removed respectively and both removed from
MCGNet. Based on the performance gain between MCGNet
and each degraded version, we conclude the effectiveness of
both CGM and MM components. To further prove the signif-
ance of MM, we also provide t-SNE visualization [Maaten
Hinton, 2008] in Figure 5 for comparing the node distri-

5 Conclusion
In this paper, we design the new task partial multi-view few-
shot learning, which explores the few-shot learning by lever-
aging the partial multi-view prior knowledge contained in the
support samples. To realize this purpose, we propose the new
Meta-alignment and Context Gated-aggregation Net-
work. Specifically, the meta-alignment and context gated-
aggregation are utilized to exploit the incomplete multi-view
prior knowledge of the support set. Based on the experimen-
tal results, our method achieves the state-of-the-art perform-
ce on two public datasets. In the future, we will extend
our study into a more difficult circumstance where the incom-
plete views exist in both query and support samples.
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