Learning Disentangled Attribute Representations for Robust Pedestrian Attribute Recognition

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Abstract

Although various methods have been proposed for pedestrian attribute recognition, most studies follow the same feature learning mechanism, i.e., learning a shared pedestrian image feature to classify multiple attributes. However, this mechanism leads to low-confidence predictions and non-robustness of the model in the inference stage. In this paper, we investigate why this is the case. We mathematically discover that the central cause is that the optimal shared feature cannot maintain high similarities with multiple classifiers simultaneously in the context of minimizing classification loss. In addition, this feature learning mechanism ignores the spatial and semantic distinctions between different attributes. To address these limitations, we propose a novel disentangled attribute feature learning (DAFL) framework to learn a disentangled feature for each attribute, which exploits the semantic and spatial characteristics of attributes. The framework mainly consists of learnable semantic queries, a cascaded semantic-spatial cross-attention (SSCA) module, and a group attention merging (GAM) module. Specifically, based on learnable semantic queries, the cascaded SSCA module iteratively enhances the spatial localization of attribute-related regions and aggregates region features into multiple disentangled attribute features, used for classification and updating learnable semantic queries. The GAM module splits attribute features into groups based on spatial distribution and utilizes reliable group attention to supervise query attention maps. Experiments on PETA, RAPv1, PA100k, and RAPv2 show that the proposed method performs favorably against state-of-the-art methods.

Introduction

Pedestrian attribute recognition aims to predict multiple attributes for one pedestrian image. Due to the wide range of applications in person re-identification (Lin et al. 2019), person retrieval (Li et al. 2018b), and scene understanding (Jaderberg et al. 2015), pedestrian attribute recognition has attracted increasing attention from industry and academia. From the perspectives of exploiting additional human knowledge and adopting attention mechanisms, numerous methods have been proposed and got significant performance improvements. However, recent works often neglect essential characteristics of pedestrian attribute recognition that distinguish it from other classification tasks (single-label classification and general multi-label classification).

We believe that the essence of pedestrian attribute recognition is two-folds.

On the one hand, unlike the single-label classification, as a sub-task of multi-label classification, pedestrian attribute recognition requires a disentangled and discriminative feature for each attribute to predict the corresponding attribute. However, almost all existing methods adopt the same feature learning manner as the single-label classification task, such as classification in ImageNet (Deng et al. 2009). For example, most works (Liu et al. 2017; Wang et al. 2017; Li et al. 2018c, 2019a; Tan et al. 2020) use the identical average-pooled image feature to classify different attributes, and some works (Zhao et al. 2018, 2019) adopt a shared attribute-group feature to classify attributes in the same group. Although these works propose various approaches and achieve promising results, we argue that it is inferior to represent different attributes with one shared and entangled feature, named by the One-shared-Feature-for-Multiple-Attributes (OFMA) mechanism. The fundamental reason for the inferiority is that, given fixed feature channel dimension, angles between the shared optimal feature learned by the OFMA mechanism and individual attribute classifiers converge to 90 degrees as the number of attributes increases, which impairs the robustness of the model. The detailed analysis is introduced in Section . As far as we know, our work is the first to reveal the limitations of this mechanism mathematically. Besides pedestrian attribute recognition, our analysis of limitations of the OFMA mechanism also applies to general multi-label classification.

On the other hand, different from general multi-label classification in COCO (Lin et al. 2014) and PASCAL-VOC (Everingham et al. 2010), in which samples of the same category can appear at any location in the image, each pedestrian attribute has a relatively consistent spatial distribution across the samples, and some attributes share similar spatial regions. For example, “Hat” and “Glasses” attributes appear at the top of the image, while “Boots” and “Sandals” locates at the bottom of the image.

However, how to exploit the two essential characteristics and incorporate them into model construction is nontrivial. To alleviate the limitations of the OFMA mechanism, we introduce the One-specific-Feature-for-One-Attribute (OFOA)
mechanism and propose a Disentangled Attribute Feature Learning (DAFL) framework as illustrated in Fig. 2. Instead of using a shared image feature, the DAFL framework extracts attribute-specific features based on precise spatial localization and representative semantic queries. Specifically, we construct learnable semantic queries and propose two complementary modules, i.e., the cascaded Semantic-Spatial Cross-Attention (SSCA) module and the group attention merging (GAM) module. The learnable semantic queries learn the unique semantic characteristic of each attribute from all samples. The cascaded SSCA module iteratively locates attribute-related spatial regions based on semantic queries and outputs query attention maps. Meanwhile, taking image feature maps as inputs and query attention maps as the affinity matrix, the cascaded SSCA module integrates spatial region features into disentangled attribute features, used for classification and updating semantic queries. To supervise the query attention map and achieve accurate localization, we divide attributes into several groups based on spatial distribution and propose the GAM module to merges qualified query attention maps into group attention memory, which is utilized as the pseudo-label. To supervise the attribute features, besides the classification loss, we construct four triplets for each attribute and apply the semantic triplet loss to achieves the compactness between positive features and discrepancy between positive and negative features.

The main contributions of our work are as follows:

• We expose the limitations of the one-shared-feature-for-multiple-attributes mechanism adopted in most existing works and propose the disentangled attribute feature learning framework, an instance of the one-specific-feature-for-one-attribute mechanism.

• We propose a cascaded semantic-spatial cross-attention module to learn discriminative feature for each attribute, which is assisted by a group attention merging module and a semantic triplet loss to improve the localization ability and robustness of the model.

• We confirm the efficacy of the proposed method by achieving state-of-the-art performance on PETA, RAPv1, PA100k, and RAPv2.

Proposed Approach

In this section, we first introduce the attribute prediction process and point out that the only determinant for attribute prediction is the angle between the shared feature vector and the classifier weight. Then, we expose the limitations of the One-shared-Feature-for-Multiple-Attributes (OFMA) mechanism adopted by most methods and propose the One-specific-Feature-for-One-Attribute (OFOA) mechanism to tackle the deficiencies in OFMA. Finally, following the OFOA mechanism, we construct the Disentangled Attribute Feature Learning (DAFL) framework and design the spatial group attention loss and semantic triplet loss.

Attribute Prediction Process

The prediction results of pedestrian attributes depend on the choice of probability thresholds. To make an intuitive and fair comparison, all existing methods set the probability threshold \( p_t = 0.5 \). Given a dataset \( D = \{x_i, y_i, |i = 1, \ldots, N\} \) and \( y_i \in \{0, 1\}^M \), for the \( j \)-th attribute of the \( i \)-th
We start from classification on two attributes, i.e., classifying a sample \((f_i, y_i)\) where \(f_i\) is the feature vector of the sample and \(y_i = \{1, 1\}\) is the ground truth label. We take classification on the positive sample of attributes as an example, and the classification on negative samples can be analyzed in the same way. Following the common practice, binary cross-entropy loss is adopted as the classification loss and other experimental settings are present in the supplementary material. Thus, the problem can be formulated as:

$$\max_h \log \left( \sigma(w_1^T f_i) \right) + \log \left( \sigma(w_2^T f_i) \right).$$  

(5)

Given the two experimental observations, we hypothesize that the classifier weights \(w_1\) and \(w_2\) are orthogonal, and their norms are the same. We prove that the optimal feature \(f\) is located in the middle of the two classifiers, i.e., the feature has the same distance from both two classifiers and the optimal angles between the shared feature and two classifiers are both 45°, as demonstrated in Fig. 1(a). The proof is available in the supplementary material. For classification on three attributes, the optimal feature has the same distance from all three classifiers, i.e., the optimal angles are 54.74°, as shown in Fig. 1(b). Furthermore, for classification on \(M\) attributes, we conclude that the optimal feature achieves a trade-off in the distance between itself and multiple classifiers to minimize the binary cross-entropy loss. This property makes the optimal angle converge to 90° as the number of attributes \(M\) increases. Specifically, on existing datasets PA100k, PETA, and RAP, the attributes \(M\) are 26, 35, 51, and the optimal angles are 78.69°, 80.27°, and 81.95° respectively, as shown in Fig. 1(c). This theoretical conclusion is verified in the experimental statistics in Fig. 3.

However, the optimal angles close to 90° in the training stage are far from our expectations. As a result, a small perturbation can make features of the test set cross the decision boundary, causing angles of the test set to be greater than 90° and yielding wrong predictions. Specifically, the learned features are susceptible to changes in pedestrian pose, illumination, and background, resulting in incorrect classifica-
In addition to the difference in spatial distribution, semantic characteristics also facilitate learning discriminative features, especially for attributes with a similar spatial distribution. Considering that the semantic characteristics are consistent across samples, we design learnable semantic queries and introduce the triplet loss on features of each attribute to further improve the discrimination of features.

The DAFL framework mainly consists of the cascaded SSCA module and the GAM module. The SSCA module is proposed to locate precise spatial regions for each attribute and aggregate region features as attribute features. Concretely, the \( s \)-th SSCA module takes semantic query \( Q^s \in \mathbb{R}^{C \times M} \) and image feature map \( \mathcal{F} \in \mathbb{R}^{C \times H \times W} \) as inputs and outputs query attention map \( A \in \mathbb{R}^{M \times H \times W} \) and attribute feature \( F^s \in \mathbb{R}^{C \times M} \), where \( M \) is the number of attributes. The channel, height, and width dimension of the feature map is represented by \( C, H, \) and \( W \) respectively. The feature map \( \mathcal{F} \) is output by the backbone network (ResNet50 (He et al. 2016)). The query attention map \( A \) is computed as follows:

\[
A = \text{Softmax}(\frac{\theta(Q)^T \phi(\mathcal{F})}{\sqrt{C}}),
\]

where \( \theta(Q) = W_{\theta}Q \) and \( \phi(\mathcal{F}) = W_{\phi}\mathcal{F} \) are two linear embedding functions. As shown in Fig. 2, query attention map highlights attribute-related spatial regions and can be used as affinity matrix to aggregate region features as specific spatial feature \( F^s \), which is formulated as:

\[
F^s = A\psi(\mathcal{F})^T,
\]

where \( \psi(\mathcal{F}) = W_{\phi}\mathcal{F} \) is a linear embedding function. Inspired by the success of the multi-head self-attention mechanism (Vaswani et al. 2017), we implement the \( A, F^s \) in a multi-head manner. To further refine the semantic query and locate reliable spatial regions, we cascade multiple SSCA modules

![Diagram of the DAFL framework and the SSCA module.](image-url)
and take attribute feature $F^{s-1}$ of the previous SSCA module as the semantic query $Q^s$ of the current SSCA module:

$$Q^s := F^{s-1},$$

where $s = 0, 1, \ldots S - 1$ and $S$ is the number of cascaded SSCA modules. The $Q^0$ is randomly initialized.

Based on semantic query $Q$, we can extract spatially disentangled attribute features $F$ from single image feature map $F$. However, due to the imbalanced attribute distribution, some minority attributes do not have enough positive samples to learn the precise query attention map $A$ and effective attribute features $F$. Inspired by the facts that some attributes have a similar spatial locations, such as “Hat” and “Glasses”, “UpperLogo” and “UpperPlaid”, “Front” and “Back”, we propose to merge query attention maps of multiple attributes with the similar spatial distribution and use the merged group attention to supervise minority attributes. Specifically, we first divide attributes into several groups $G$ based on the spatial distribution. Then, we propose the group attention merging (GAM) module to merge qualified query attention maps $A_{i,m}$ into group attention $G^a_i = \{G_k^a| k = 1, \ldots, K\} \in R^{K \times H \times W}$ as follows:

$$G_k^a = \frac{1}{|G_k|} \sum_{m \in G_k} \frac{1}{|R|} \sum_{i=1}^{b} \mathbb{1}\{r\} A_{i,m},$$

where $i$ denotes the sample index, $b_i$ indicates the batch size, $\mathbb{1}\{\cdot\}$ is the indicator function, and $\cdot | \cdot$ represents the set cardinality. The condition set $R = \{r|logit(s_i,m) > \tau, y_{i,m} = 1\}$ and the hyper-parameter $\tau$ are adopted to select qualified query attention maps for each attribute from the current batch. $K$ is a pre-defined group number and set to $K = 6$ as default. For example, given attribute groups of PA100k as listed in Tab. 1, for group attention $G^a_i$, we first sum the qualified query attentions of “Hat” and “Glasses” in a batch to respectively obtain a “Hat” attention and a “Glasses” attention. Then, two attentions are merged into “Head” group attention based on group $G_1$.

To mitigate the fluctuation caused by limited batch size and random sampling, we maintain a spatial group memory $G^m_k$ in a momentum updated way to make the group attention reliable and consistent across batches. The $G^m_k$ is formulated as:

$$G^m_k \leftarrow \theta \times G^m_k + \alpha \times G^a_k,$$

where $\theta \in (0, 1]$ is the momentum hyper-parameter. We take the group attention $G^m_k$ as the pseudo-label to supervise the inaccurate query attention map $A_{i,m}$ of attributes in the group $G_k$. Thus, we propose the group consistency loss to rectify the imprecise spatial localization of minority attributes:

$$L_{group} = \frac{1}{b_i} \| \sum_{m \in G_k} \sum_{i=1}^{K} \mathbb{1}\{r\} G^m_k - A_{i,m} \|_2.$$
Comparison to the State of the Arts

In Tab. 2, we compare the performance between our proposed methods and recent SOTA methods on PETA, RAPv1, PA100k, and RAPv2 to show the superiority of our methods. Since some methods (Wang et al. 2017; Li et al. 2019b) adopt the model ensemble policy in the inference stage, we do not list their performance to make a fair comparison. In the label-based metric mA, we achieve SOTA performance and outperform the JLAC method by 0.11%, 0.03%, 1.23%, 1.81% on four datasets. In four instance-based metrics, our method DAFL achieves SOTA performance on the two largest datasets PA100k and RAPv2, and comparable performance on small datasets RAP and PETA. Our method achieves better performance on the label-based metric than those on the instance-based metrics for two reasons. One is that the bottleneck of the mA metric lies in the attributes with a small number of positive samples. The other is that the GAM module and semantic triplet loss of our method can alleviate the imbalance of attribute distribution. In addition, we find that our proposed method achieves better performance on large datasets (90,000 and 67,943 training images on PA100k and RAPv2 respectively) than on small datasets (33,268 and 11,400 training images on PETA and RAPv1 respectively). This phenomenon due to the fact that the effective semantic queries and reliable spatial group memory require more samples to learn.

Ablation Study

As shown in Tab. 3, we investigate the effect of the cascaded SSCA module, GAM module (with spatial consistency loss), and semantic triplet loss. To make a fair and convincing evaluation, we conduct ablation experiments on the largest dataset PA100k (Liu et al. 2017), which follows the zero-shot pedestrian settings and can truly validate the generalization of the model (Jia et al. 2021). For the mA and F1 metric, the cascaded SSCA module alone can achieve 1.50% and 0.40% performance improvement separately. Combining the GAM and TripletLoss into the cascaded SSCA module can further improve the performance by 1.33%, 0.65% in mA and F1.

To further validate the rationality of proposed spatial consistency loss, we implement a variant GAM* of our method.
Figure 3: Angle distribution of the baseline model and our proposed method on each attribute. We show angle distribution on each attribute of the baseline model (blue box) and our proposed method (red box). The upper and lower green dashed lines mark the theoretical optimal angle (78° on PA100k) and the angle decision boundary (90°), respectively.

To supervise the query attention map $Q$ of each attribute, the GAM* module maintains a specific spatial memory for each attribute instead of using the group memory shared by multiple attributes. We report the performance of the variant in the second last row of Tab. 3. On the one hand, the performance improvement achieved by the GAM and GAM* module proves the effectiveness of spatial consistency loss. On the other hand, since the GAM module considers the insufficiency in positive samples of minority attributes, it can alleviate the distribution imbalance of attributes and achieve better performance than the GAM* module.

Experiments results on the number of the cascaded SSCA module are listed in Tab 4. As $S$ increases, the performance first increases when $S < 3$ and then decreases when $S > 3$. We argue that the cascaded SSCA module is beneficial for discriminative semantic queries and accurate query attention map when $S$ is small. However, the semantic query $Q_s$ of the current step is the attribute feature $F^{s-1}$ of the previous step, which is aggregated from the feature map $F$. Thus, when $S$ is large, the number of pixels in the feature map similar to the semantic query gradually increases, and the degree of similarity also increases. As a result, the query attention map $A$ cannot highlight the attribute-related regions but focuses on the whole foreground regions, excluding the background.

| Cascade Number | mA    | Accu  | Prec  | Recall | F1    |
|----------------|-------|-------|-------|--------|-------|
| $S = 1$        | 82.82 | 79.89 | 87.29 | 88.50  | 87.63 |
| $S = 2$        | 83.31 | 79.46 | 86.21 | 89.10  | 87.89 |
| $S = 3$        | 83.54 | 80.13 | 87.01 | 89.19  | 88.09 |
| $S = 4$        | 83.01 | 79.49 | 86.40 | 88.95  | 87.66 |
| $S = 5$        | 83.13 | 79.60 | 86.83 | 88.56  | 87.69 |
| $S = 6$        | 82.73 | 79.44 | 86.64 | 88.69  | 87.65 |

Table 4: Experiments on the number $S$ of the cascaded SSCA modules.

Figure 4: Prediction on images with marginal pose variation. Due to the small angles between features and classifiers, our method shows superior robustness than the baseline model.

Conclusion

This paper exposes the limitations in the OFMA mechanism and proposes the discriminative and robust attribute feature learning framework for pedestrian attribute recognition, which follows the OFOA mechanism. The proposed framework makes full use of distinctions between attributes from the spatial distribution and semantic characteristics to extract a specific feature for each attribute. Our proposed method achieves outstanding performance consistently on the PETA, RAPv1, PA100K, and RAPv2.

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