Abstract
Transformers have shown preferable performance on many vision tasks. However, for the task of person re-identification (ReID), vanilla transformers leave the rich contexts on high-order feature relations under-exploited and deteriorate local feature details, which are insufficient due to the dramatic variations of pedestrians. In this work, we propose an Omni-Relational High-Order Transformer (OH-Former) to model omni-relational features for ReID. First, to strengthen the capacity of visual representation, instead of obtaining the attention matrix based on pairs of queries and isolated keys at each spatial location, we take a step further to model high-order statistics information for the non-local mechanism. We share the attention weights in the corresponding layer of each order with a prior mixing mechanism to reduce the computation cost. Then, a convolution-based local relation perception module is proposed to extract the local relations and 2D position information. The experimental results of our model are superior promising, which show state-of-the-art performance on Market-1501, DukeMTMC, MSMT17 and Occluded-Duke datasets.

Introduction
Person re-identification (ReID) aims to identify the same person from a set of pedestrian images captured by multiple cameras. This task is very challenging, since the attributes (e.g., clothing, gender, hair) of pedestrians vary dramatically and their pictures are taken under various conditions (e.g., illumination, occlusion, background clutter, and camera type). Hence, learning distinctive and robust features plays a decisive role in the field of person ReID.

CNN-based methods (Luo et al. 2019) have achieved great success in this field due to their strong ability in extracting deep discriminative features. In order to mine fine-grained local information from different body parts, part-based methods (Yao et al. 2019) are proposed to extract part-informed representations. By partitioning the backbone network’s feature map horizontally into multiple parts (Fu et al. 2019; Sun et al. 2018) as shown in Figure 1(a), the deep neural networks can concentrate on learning more fine-grained salient features in each individual local part. However, due to the hard inductive bias of CNN, their models suffer from one common drawback, i.e., they require relatively well-aligned body parts for the same person. Besides, strict uniform partitioning of the feature map breaks with-part consistency.

Attention-based methods alleviate these problems (Cai, Wang, and Cheng 2019) by locating human parts automatically as shown in Figure 1(b). However, they consider only coarse region-level attention whilst ignoring fine-grained pixel-level saliency and relational information.

Recently, with the success of Transformers in a variety of vision tasks, some previous work (He et al. 2021; Li et al. 2021a) has attempted to introduce the power of self-attention
mechanism into ReID. By cutting the image into patches, transformers are capable of globally attending all the patches at every layer, making the spatial correspondences between input and intermediate features weaker. Nevertheless, most of the models obtain the attention matrices based on pairs of queries and isolated keys at each spatial location as shown in Figure 1(c), while leaving the rich contexts on high-order feature relations under-exploited. Moreover, although vision transformers can capture long-distance feature dependencies, they deteriorate local feature details (Peng et al. 2021) (Li et al. 2021b). This low-capacity representation is not robust to pedestrians with dramatic variations. In addition, the performance of Transformers still lags behind CNNs in the low data regime (Dosovitskiy et al. 2020) since vanilla Transformers lack certain desirable inductive biases processed by CNNs (Dai et al. 2021; d’Ascoli et al. 2021; Guo et al. 2021), such as locality and weight sharing. These drawbacks clearly limit the application of Transformers on the ReID task.

To solve these problems, we propose a novel Transformer-based model, i.e. Omni-Relational High-Order Transformer (OH-Former), which is equipped with a high-order transformer module with a prior mixing attention weight sharing mechanism and a local relation perception module (LRP). Specifically, we first obtain the first-order relation information by computing the non-local relations from pairs of queries and all other isolated keys at each spatial location, which named basic relations (Zhou et al. 2021). Then we leverage the LRP which consists of a deformable and depth-wise convolution branch to dynamically model the local fine-grained feature relations and 2D spatial positions, which we call local relations. After that, by modeling the correlations of the positions in the feature map using non-local operations, the proposed module can integrate the local information captured by convolution operations and first-order long-range dependency captured by non-local operations. We call this robust feature representation as the omni-relational high-order feature, which contains both the high-order non-local information and the local detailed information as shown in Figure 1(d). For example, given a pedestrian image, there are some noticeable signals on blue and yellow dots for the red dot. After constructing the basic and local relations, the correlations among them are then captured by computing self-attention for the tokens. Using this mechanism, we explicitly tell the model that there are correlations among those tokens, the detailed information around the signals, the long-range fused information for those signals. Then the latter layers will learn under which circumstances such correlations are related to the identity information of the person.

High-order statistics can improve the model classification performance (Li et al. 2018; Lin, RoyChowdhury, and Maji 2015), but they lead to high-dimensional representation and expensive computation cost simultaneously. Although the token number in our high-order layer is small enough after the aggregation of LRP, the $O(n^2)$ non-local computation cost cannot be ignored. For efficient modeling, we propose a Prior Mixing Attention Sharing Mechanism to reduce the computation cost and model the dominant and diverse features.

In summary, the contributions of this paper are as follows:

1. We propose a novel high-order transformer module that explores high-order relation information for person ReID. To the best of our knowledge, OH-Former is the first work to explore high-order information in Transformer.

2. We propose a Prior Mixing Attention Weights Sharing Mechanism to reduce the computation cost and model the dominant and diverse features.

3. To incorporate with the inductive biases of CNNs, we design a local relation perception module (LRP) to extract and aggregate the local information.

4. Comprehensive experiments on four person ReID benchmark datasets demonstrate that our proposed model OH-Former achieves state-of-the-art performance.

**Related Works**

**Person Re-identification**

Several person ReID methods based on CNNs have recently been proposed. To extract fine-grained features from different body parts, they often utilize part-based methods (Yao et al. 2019) to enhance the discriminative capabilities of various body parts. The fine-grained parts are usually generated by roughly horizontal stripes (Sun et al. 2018; Fu et al. 2019; Wang et al. 2018; He et al. 2018). They require relatively well-aligned body parts for the same person. However, person pictures localized by the off-the-shelf object detectors often have the spatial semantics misaligned problem. Other methods make use of external cues such as pose (Zheng et al. 2019; Miao et al. 2019; Wang et al. 2020a; Gao et al. 2020), parsing (Kalayeh et al. 2018; He et al. 2019; He and Liu 2020) information to align body region across images. These approaches usually require extra sub-networks and computation cost in inference and the accuracy is limited to the power of the estimator. Attention-based methods (Li, Zhu, and Gong 2018; Liu et al. 2017; Cai, Wang, and Cheng 2019) learn feature representations robust to background variations and focus on most informative body parts, however, they are not capable of modeling fine-grained information and relations. Thus, transformer-based methods are introduced to explore the power of self-attention to model robust person feature representation.
Vision Transformers

With the success of Transformers [Vaswani et al. 2017], in natural language processing, many studies [Dosovitskiy et al. 2020, Chen et al. 2021, Touvron et al. 2021] have shown that they can be applied in computer vision as well. Transformer-based methods have boosted various vision tasks such as image classification [Yuan et al. 2021], object detection [Carion et al. 2020, Zhu et al. 2020b], and segmentation [Xie et al. 2021]. Recently, some work [He et al. 2021a, Wu et al. 2021] explores the power of transformers in the field of ReID. However, they do not consider the subtle high-order representation differences among pedestrians which is missing in the vanilla transformers.

More importantly, transformers show preferable performance on large datasets while lagging behind CNNs in the low data regime since they lack the inductive biases which is inherent in CNNs [Dosovitskiy et al. 2020, Dai et al. 2021], e.g. locality and translation equivariance. To solve this problem, previous work [Peng et al. 2021, Li et al. 2021b, Guo et al. 2021, d’Ascoli et al. 2021, Li et al. 2021c] attempts to introduce convolutions to Transformers to employ all the benefits of CNNs while keeping the advantages of Transformers. However, their designs only introduce 2D locality but ignore local feature similarity, i.e., local relations. It will damage Transformers’ representation obtained from self-attention. In contrast, our model is aware of local relations by augmenting the spatial sampling locations with learned offsets [Dai et al. 2017].

High-Order Information

The high-order statistics have been successfully exploited in fine-grained visual classification tasks [Zhou et al. 2021, Li et al. 2018, Lin, Roy-Chowdhury, and Maji 2015]. For the ReID task, Chen, Deng, and Hu (2019) models high-order attention statistics information to capture the subtle differences. Zhang et al. (2021) introduces a second-order information bottleneck to cope with redundancy and irrelevance features. Xia et al. (2019) models local features’ long-range relationships. Wang et al. (2020b) learns high-order topology information for occluded ReID. However, non of them consider the high-order statistics of non-local information which is important for modeling pedestrians. We instead model an omni-relational feature to capture both the local and non-local relation differences among pedestrians.

Proposed Method

Overall Architecture

The overview of OH-Former is presented in Figure 2. Given an image of \( x \in \mathbb{R}^{H \times W \times C} \), where \( H, W, C \) denote the image’s height, width, and channel number, respectively. We utilize the stem architecture as our patch embedding layer which has a \( 5 \times 5 \) convolution with stride 5 to reduce the feature size, followed by a \( 3 \times 3 \) convolution with stride 2 for better local information extraction [Guo et al. 2021] to get a 2D feature \( x \in \mathbb{R}^{h \times w \times c} \). Then we flatten the feature into a sequence of tokens \( X \in \mathbb{R}^{n \times d} \), where \( n = h \times w \) is the resulting number of patches and \( d \) is the channel number. Following the design of [Dosovitskiy et al. 2020], we concatenate a class token to those tokens and add a learnable position embedding on them. Afterwards, we process those tokens \( X \in \mathbb{R}^{T \times d} \) with stacked Multi-head Self-Attention (MHSA) and our OH-Former layers. The resulting tokens without class token \( z_{cls} \) are passed to an adaptive average pooling layer [Sun et al. 2018] to get part tokens \( z_i (i = 1, 2, \ldots, p) \), where \( p \) is the number of parts.

Finally, we optimize the network by minimizing the sum of Cross-Entropy and Triplet losses with BNNeck [Luo et al. 2019] over the class and part tokens. Specifically, our model is optimized with the following losses:

\[
L = L_{CE}(z_{cls}) + L_{Triplet}(z_{cls}) + \frac{1}{p} \sum_{i=1}^{p} (L_{CE}(z_i) + L_{Triplet}(z_i))
\]

where triplet loss is computed as \( L_{Triplet} = [d_p - d_n + \alpha] \).\( d_p, d_n \) are feature distances of positive pair and negative pair, respectively. \( \alpha \) is the margin parameter.

During inference, we concatenate the class and part tokens to form the final feature representation and compute the Euclidean distances between them to determine the identities of different people.

Omni-Relational High-Order Transformer

In this section, we will describe our proposed OH-Former layer in details.

First-Order Self-Attention. Given an input sequence \( X \in \mathbb{R}^{T \times d} \), the first-order self-attention performs a scaled dot product attention following the vanilla Transformer [Vaswani et al. 2017, Dosovitskiy et al. 2020], defined as:

\[
S_1 = \frac{Q_1 (K_1)^T}{\sqrt{d_k}}, s.t. Q_1 = X W^{Q_1}, K_1 = X W^{K_1}
\]

where \( W^{Q_1} \in \mathbb{R}^{T \times d_k}, W^{K_1} \in \mathbb{R}^{d \times d_k} \) are linear transformations. \( S_1 \) is an \( l \times 1 \) matrix, entry \( (i, j) \) represents the similarity between position \( i \) and position \( j \). For simplicity, the multi-head self-attention mechanism is omitted here.
**Local Relation Perception Module.** Although vision transformers can capture long-distance feature dependencies, they ignore the local feature details (Yuan et al. 2021). Fortunately, convolutions’ hard inductive biases encoded by locality and weight sharing can compensate for this drawback (Peng et al. 2021). Previous methods have introduced inductive bias to Transformers by fixed grid depthwise convolution (Li et al. 2021b,c; Dai et al. 2021), which are unaware of local relations. They actually bring in 2D positions, leading to transformers (Xie et al. 2021). In contrast, we propose a Local Relation Perception Module (LRP), which consists of deformable (Dai et al. 2017) and depthwise convolution (Tan and Le 2019) branches as shown in Figure 3. The deformable convolution branch dynamically aggregates local relation information across patches by attending to sparse spatial locations, producing the refined local-relation-aware feature. The depthwise convolution branch uses a fixed 3 × 3 depthwise convolution with stride 2 to extract positional information (Chu et al. 2021; Xie et al. 2021) for high-order features. Specifically, LRP is defined as:

\[ LRP(A_i) = DeformConv(A_i) + DWConv(A_i) \]  

(4)

where \(A_i\) is the i-th order feature. \(DeformConv()\) denotes the deformable convolution and \(DWConv()\) denotes the depth-wise convolution. Without loss of generality for other Transformer variants, we feed the first-order features without class token to our LRP. For simplicity, the reshape operations are omitted here.

**Omni-Relational High-Order Self-Attention.** After capturing the basic and local relations, we take a step further to model our Omni-relational high-order features. For constructing the relations among basic and local relations, we use multi-head self-attention to process features processed by LRP. Given the i-th order features \(A_i\), the (i+1)-th order information \(A_{i+1}\) is extract by

\[ S_{i+1} = Q_{i+1} (K_{i+1})^T \sqrt{d_k} \]

(5)

\[ A_{i+1} = Softmax(S_{i+1}) \cdot V_{i+1} \]

(6)

where \(Q_{i+1} = A_i W^Q, K_{i+1} = A_i W^K, V_{i+1} = A_i W^V\). After that, \(A_{i+1}\) is processed by LRP again for computing higher-order self-attention.

Compared to OH-Former, vanilla transformers can also capture high-order statistics, but they need to stack many layers which leads to high computation cost, and deep transformers are very hard to train.

**Prior Mixing Attention Sharing Mechanism.** Although the number of tokens in high-order layer is small enough after being aggregated by LRP, the \(O(n^2)\) self-attention computation cost is still too high. For efficient modeling, we propose a Prior Mixing Attention Sharing Mechanism for each order within an OH-Former layer. The idea is that we only compute the weight matrix once and reuse it in high-order layers.

Intuitively, we want the high-order self-attention to extract high-order information for each location, so the spatial correspondence relationship should be guaranteed for each order within an OH-Former layer. And we compute JS divergence to measure the similarity between the high-order and the first-order self-attention weights. Figure 4(b) shows that the model generates similar weights over orders. Thus, we can share \(S_1\) without class token similarity to high-order layers:

\[ S_i = S_1, i = 2, ... \]

(7)

Moreover, person images have some fixed pattern for identification which can serve as a prior. To aggregate dominant and diverse information, we propose a prior mixing mechanism. After computing attention from inputs (e.g., \(Softmax(QK^T)\)), the attention is further augmented by a learned prior. Specifically, the Prior Mixing Attention Sharing Mechanism is defined as:

\[ S_i = S_1 \cdot W, i = 2, ... \]

(8)

where \(W\) is the learnable parameters.
A zero-value vector which has the same shape as the reshaped first-order feature.

OH-Former and OH-Former share insight on this in the ablation studies chapter. The setting of OH-Former is still flexible. So we show our patterns in the low-level layer (d’Ascoli et al. 2021), the or-non-local operations and they need to extract simple context lean high-order statistics in the high-level layer by stacking.

2) The DukeMTMC-reID (Ristani et al. 2016) composed of 36 441 images of 1404 identities. 3) The MSMT17 (Wei et al. 2018) containing 126 441 images of 4101 identities. 4) The Occluded-Duke dataset (Miao et al. 2019) with occluded person images selected from DukeMTMC-reID.

Implementation

Training. All person images are resized to 368 × 128. The training images are augmented with random horizontal flipping and random erasing. The batch size is set to 256 with 16 images per ID. Stochastic gradient descent optimizer (SGD) is employed with momentum of 0.9 and weight decay of 1 × 10^{-4}. The learning rate is initialized as 0.01 with cosine learning rate decay. For the MHSA and first-order self-attention layers, we use the imagenet-pretrained model of ViT-B (Dosovitskiy et al. 2020). Our model is implemented with PyTorch library (Paszke et al. 2017) and trained on four Nvidia Titan X GPUs.

Evaluation Protocols. We use standard metrics in ReID community, namely Cumulative Matching Characteristic (CMC) curves and mean Average Precision (mAP), to evaluate all methods. We report ReID results under the setting of a single query for a fair comparison.

Ablation Study of LRP

The effectiveness of the proposed LRP Module is validated in Table 2. We compare the performance of several variants of our LRP in terms of mAP and rank-1 accuracy. From the first three rows, we can see that convolution improves the retrieval performance by introducing 2D position information. Although its fixed grid convolution kernel can capture local information, it is unaware of local relation. Thus, for dynamically aggregating high-order information which has complex relations aggregated by non-local operations, a local-relation-aware operation is critical to our model. Also, the worst result in the first row demonstrates that without local downsampling operations the high-order self-attention will learn homogeneous information and the effective of our LRP is significant. From the fourth, fifth and seventh rows, we show that compared with convolution, pooling operations will lead to the loss of large amount of information. This is due to the fact that local information in non-local operations is more complex than it is in CNN features, not only because pooling is an parameter-free operation. The second, sixth and last rows show exploring local relations to construct our omni-relational feature is important, and the performance reaches to the peak when using all components.

Ablation Study of OH-Former

We demonstrate the effectiveness of the proposed OH-Former layer in Table 3. From the second row, we can observe that high-order information will slightly decrease the performance since Transformers need to learn simple context patterns on the low level. The third row shows that high-order statistics can only brings a small performance boost since vanilla Transformers can learn high-order statistics in the high level layers by stacking transformer layers. Thus, the model benefits more in the middle levels as shown in the
Table 1: Performance comparison with state-of-the-art methods in holistic ReID. The best two results are in bold and underline.

| Method                  | DukeMTMC-reID | Market1501 | MSMT17 |
|-------------------------|---------------|------------|--------|
|                         | mAP R-1       | mAP R-1    | mAP R-1|
| HACNN (Li et al. 2018)  | 63.8          | 80.5       | -      |
| PCB (Sun et al. 2018)   | 66.1          | 81.7       | -      |
| CBN (Zhuang et al. 2020)| 67.3          | 82.5       | -      |
| PCB+RPP (Sun et al. 2018)| 69.2        | 83.3       | -      |
| HPM (Fu et al. 2019)    | 74.3          | 86.6       | -      |
| GASM (He et al. 2020)   | 74.4          | 88.3       | -      |
| CTF (Zhang et al. 2021) | 74.4          | 87.4       | -      |
| SAN (Jin et al. 2020)   | 76.4          | 86.4       | -      |
| MHN (Wang et al. 2018)  | 77.2          | 89.1       | -      |
| MGN (Wang et al. 2018)  | 78.4          | 88.7       | -      |
| SCSN (Chen et al. 2020) | 79.0          | **91.0**   | -      |
| ViT-BoT (He et al. 2021)| 79.3          | 88.8       | -      |
| ISP (Zhu et al. 2020a)  | 80.0          | 89.6       | -      |
| TransReID (He et al. 2021)| 82.6        | 90.7       | -      |
| OH-Former (Ours)        | **82.8**      | **91.0**   | -      |
| OH-Former (Share)       | **82.8**      | **91.0**   | -      |

Table 2: Performance comparison with different variants of LRP on DukeMTMC-reID dataset. DWC: Depthwise Convolution; AP: Average Pooling; MP: Max Pooling; NC: Normal Convolution; DFC: Deformable Convolution. None means we do not add any downsampling operation after the self-attention operation.

| LRP Type | mAP R-1 |
|----------|---------|
| None     | 80.1 89.4 |
| DWC      | 81.7 90.2 |
| NC       | 81.8 90.1 |
| AP       | 80.7 89.9 |
| MP       | 80.4 89.7 |
| DWC + AP | 81.8 90.2 |
| AP + DFC | 82.3 90.8 |
| DWC + DFC (Ours) | **82.8** 91.0 |

Table 3: Ablation results for the OH-Former with different orders on DukeMTMC-reID dataset. $H^i_j$ means we use an i-order OH-Former layer at the j-th layer. Note that we only show OH-Former layers for simplicity.

| OH-Former order | mAP R-1 |
|-----------------|---------|
| [None]          | 78.6 88.9 |
| $[H^1_2]$       | 78.5 88.9 |
| $[H^0_2]_{10,11}$ | 78.8 89.0 |
| $[H^2_2,4,6,8]$ | 82.4 90.9 |
| $[H^2_2,4,6,8]$ | **83.0** 91.2 |
| $[H^2_2,4,6,8]$ | **82.9** 91.3 |
| $[H^2_2,4,6,8]$ | 82.8 91.0 |

Table 4: Ablation results for the proposed OH-Former on DukeMTMC-reID dataset. LRP: Local Relation Perception module for OH-Former layer. OH: OH-Former layer. AS: Attention Sharing. PM: Prior Mixing.

| Method | LRP OH AS PM | mAP R-1 |
|--------|--------------|---------|
| Baseline | × × × × | 78.6 88.9 |
| OH-Former w/o LRP | × ✓ × × | 80.1 89.4 |
| OH-Former | ✓ ✓ × × | **82.8** 91.0 |
| OH-Former Share w/o PM | ✓ ✓ ✓ | 80.3 90.0 |
| OH-Former Share | ✓ ✓ ✓ ✓ | **81.9** 90.2 |

Comparison with State-of-the-Art Methods

Results on Holistic Datasets. In Table 1 we compare our proposed OH-Former and OH-FormerShare with the last five rows. And the order higher than three in OH-Former layer just delivers a negligible boost as shown in the sixth row. As a result, we choose the configuration $[H^2_2,4,6,8, H^3_4]$ in the last row to trade off speed and performance.

Ablation experiments from overall and individual perspectives are also conducted on our proposed method. Our OH-Former layers bring 5.34% mAP improvement over the baseline by modeling omni-relational high-order features. OH-Former achieves the best performance, which shows that advantages of LRP and OH-Former layer are complementary and their coherent innovations contribute to a high-performance ReID model. The forth row shows that Attention Weights Sharing will decrease the model performance. But after adding our Attention Prior (PM), the model shows comparable performance to our OH-Former model by fusing dominant and diverse information.
state-of-the-art ReID methods. On DukeMTMC-reID, we can see that OH-Former obtains the highest mAP (82.8\%) and R-1 (91.0\%) with 0.2–16.7\% and 0.3–9.3\% improvements compared to other methods, respectively. On Market1501 and MSMT17, OH-Former achieves comparable performance with the latest methods, especially on the R-1 metric. As for the OH-Former\_Share, it surpasses all methods except TransReID by a considerable improvement (at least +1.9\%/+6.6\% mAP) on DukeMTMC-reID/MSMT17.

**Results on Occluded Dataset.** To further explore the generalization ability of ReID models in a complex environment, we utilize the training set of Market1501 to train our model and directly test it on Occluded-Duke dataset. The performance comparison is shown in Table 5. On Occluded-Duke dataset, both OH-Former and OH-Former\_Share outperform the previous state-of-the-art methods by 1.6–23.5\% and 0.4–22.3\% in mAP, yielding a result of 60.8\% and 59.6\% in mAP, respectively. The above fact indicates that our proposed method has outstanding robustness for complex ReID tasks, e.g., occlusion ReID.

Our model constructs an universal representation that can deal with pedestrians with large variations and even unseen pedestrians as shown in Table 5 instead of mapping images to a feature space with small intra-identity distance and large inter-identity distance through learning specific inductive bias, e.g., part correspondence (Sun et al. 2018), part relations (Park and Ham 2020; He et al. 2021), our model embeds person images by considering all-order features for both local and non-local relations and learning inductive bias by itself. Thus our omni-relational high-order features are robust to all kinds of variations.

| Method         | mAP  | R-1  |
|----------------|------|------|
| PGFA (Miao et al. 2019) | 37.3 | 51.4 |
| HORelD (Wang et al. 2020) | 43.8 | 55.1 |
| ISP (Zhu et al. 2020a) | 52.3 | 62.8 |
| TransReID (He et al. 2021) | 59.2 | 66.4 |
| OH-Former\_Share (Ours) | 59.6 | 66.7 |
| OH-Former (Ours) | **60.8** | **67.1** |

Table 5: Performance comparison with state-of-the-art methods on Occluded-Duke dataset.

**Conclusion**

In this paper, We present a transformer-based model (OH-Former) for person ReID which takes into account the omni-relational high-order statistics on body tokens, thus making global class and local part tokens discriminative. Furthermore, we propose a Prior Mixing Attention Sharing Mechanism for our OH-Former layer to reduce the computation cost. The local relation perception module introduces inductive biases to augment local information. The effectiveness of each proposed component is sufficiently validated by the ablation studies. The experimental results on various benchmark datasets show that the proposed OH-Former achieves state-of-the-art performance.

References

Cai, H.; Wang, Z.; and Cheng, J. 2019. Multi-scale body-part mask guided attention for person re-identification. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops, 0–0.

Carion, N.; Massa, F.; Synnaeve, G.; Usunier, N.; Kirillov, A.; and Zagoruyko, S. 2020. End-to-end object detection with transformers. In Proceedings of the European Conference on Computer Vision, 213–229.

Chen, B.; Deng, W.; and Hu, J. 2019. Mixed high-order attention network for person re-identification. In Proceedings of the IEEE International Conference on Computer Vision, 371–381.

Chen, H.; Wang, Y.; Guo, T.; Xu, C.; Deng, Y.; Liu, Z.; Ma, S.; Xu, C.; Xu, C.; and Gao, W. 2021. Pre-trained image processing transformer. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 12299–12310.

Chen, X.; Fu, C.; Zhao, Y.; Zheng, F.; and Yang, Y. 2020. Salience-Guided Cascaded Suppression Network for Person Re-Identification. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition.

Chu, X.; Tian, Z.; Zhang, B.; Wang, X.; Wei, X.; Xia, H.; and Shen, C. 2021. Conditional positional encodings for vision transformers. arXiv preprint arXiv:2102.10882.

Dai, J.; Qi, H.; Xiong, Y.; Li, Y.; Zhang, G.; Hu, H.; and Wei, Y. 2017. Deformable convolutional networks. In Proceedings of the IEEE International Conference on Computer Vision, 764–773.

Dai, Z.; Liu, H.; Le, Q. V.; and Tan, M. 2021. CoAtNet: Marrying convolution and attention for all data sizes. arXiv preprint arXiv:2106.04803.

d’Ascoli, S.; Touvron, H.; Leavitt, M.; Morcos, A.; Biroli, G.; and Sagun, L. 2021. Convit: Improving vision transformers with soft convolutional inductive biases. arXiv preprint arXiv:2103.10697.

Dosovitskiy, A.; Beyer, L.; Kolesnikov, A.; Weissenborn, D.; Zhai, X.; Unterthiner, T.; Dehghani, M.; Minderer, M.; Heigold, G.; Gelly, S.; et al. 2020. An image is worth 16x16 words: Transformers for image recognition at scale. arXiv preprint arXiv:2010.11929.

Fu, Y.; Wei, Y.; Zhou, Y.; Shi, H.; Huang, G.; Wang, X.; Yao, Z.; and Huang, T. 2019. Horizontal pyramid matching for person re-identification. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 33, 8295–8302.

Gao, S.; Wang, J.; Lu, H.; and Liu, Z. 2020. Pose-guided visible part matching for occluded person ReID. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 11744–11752.

Guo, J.; Han, K.; Wu, H.; Xu, C.; Tang, Y.; Xu, C.; and Wang, Y. 2021. CMT: Convolutional Neural Networks Meet Vision Transformers. arXiv preprint arXiv:2107.06263.

Guo, M.; Zhang, Y.; and Liu, T. 2019. Gaussian transformer: a lightweight approach for natural language inference. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 33, 6489–6496.
He, L.; Liang, J.; Li, H.; and Sun, Z. 2018. Deep spatial feature reconstruction for partial person re-identification: Alignment-free approach. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 7073–7082.

He, L.; and Liu, W. 2020. Guided saliency feature learning for person re-identification in crowded scenes. In Proceedings of the European Conference on Computer Vision, 357–373.

He, L.; Wang, Y.; Liu, W.; Zhao, H.; Sun, Z.; and Feng, J. 2019. Foreground-aware pyramid reconstruction for alignment-free occluded person re-identification. In Proceedings of the IEEE International Conference on Computer Vision, 8450–8459.

He, S.; Luo, H.; Wang, P.; Wang, F.; Li, H.; and Jiang, W. 2021. Transreid: Transformer-based object re-identification. arXiv preprint arXiv:2102.04378.

Jin, X.; Lan, C.; Zeng, W.; Wei, G.; and Chen, Z. 2020. Semantics-aligned representation learning for person re-identification. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 34, 11173–11180.

Kalayeh, M. M.; Basaran, E.; Gökmen, M.; Kamasak, M. E.; and Shah, M. 2018. Human semantic parsing for person re-identification. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 1062–1071.

Li, P.; Xie, J.; Wang, Q.; and Gao, Z. 2018. Toward faster training of global covariance pooling networks by iterative matrix square root normalization. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 947–955.

Li, W.; Zhu, X.; and Gong, S. 2018. Harmonious attention network for person re-identification. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2285–2294.

Li, Y.; He, J.; Zhang, T.; Liu, X.; Zhang, Y.; and Wu, F. 2021a. Diverse part discovery: Occluded person re-identification. With part-aware transformer. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2898–2907.

Li, Y.; Yao, T.; Pan, Y.; and Mei, T. 2021b. Contextual transformer networks for visual recognition. arXiv preprint arXiv:2107.12292.

Li, Y.; Zhang, K.; Cao, J.; Timofte, R.; and Van Gool, L. 2021c. Localvit: Bringing locality to vision transformers. arXiv preprint arXiv:2104.05707.

Lin, T.-Y.; RoyChowdhury, A.; and Maji, S. 2015. Bilinear cnn models for fine-grained visual recognition. In Proceedings of the IEEE International Conference on Computer Vision, 1449–1457.

Liu, X.; Zhao, H.; Tian, M.; Sheng, L.; Shao, J.; Yi, S.; Yan, J.; and Wang, X. 2017. Hydraplus-net: Attentive deep features for pedestrian analysis. In Proceedings of the IEEE International Conference on Computer Vision, 350–359.

Luo, H.; Gu, Y.; Liao, X.; Lai, S.; and Jiang, W. 2019. Bag of tricks and a strong baseline for deep person re-identification. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops, 0–0.

Miao, J.; Wu, Y.; Liu, P.; Ding, Y.; and Yang, Y. 2019. Pose-guided feature alignment for occluded person re-identification. In Proceedings of the IEEE International Conference on Computer Vision, 542–551.

Park, H.; and Ham, B. 2020. Relation network for person re-identification. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 34, 11839–11847.

Paszke, A.; Gross, S.; Chintala, S.; Chanan, G.; Yang, E.; DeVito, Z.; Lin, Z.; Desmaison, A.; Antiga, L.; and Lerer, A. 2017. Automatic differentiation in pytorch. In Proceedings of the International Conference on Neural Information Processing Systems Workshop.

Peng, Z.; Huang, W.; Gu, S.; Xie, L.; Wang, Y.; Jiao, J.; and Ye, Q. 2021. Conformer: Local features coupling global representations for visual recognition. arXiv preprint arXiv:2105.03889.

Ristani, E.; Solera, F.; Zou, R.; Cucchiara, R.; and Tomasi, C. 2016. Performance measures and a data set for multi-target, multi-camera tracking. In Proceedings of the European conference on computer vision, 17–35.

Sun, Y.; Zheng, L.; Yang, Y.; Tian, Q.; and Wang, S. 2018. Beyond part models: person retrieval with refined part pooling (and a strong convolutional baseline). In Proceedings of the European Conference on Computer Vision, 480–496.

Tan, M.; and Le, Q. 2019. Efficientnet: Rethinking model scaling for convolutional neural networks. In Proceedings of the International Conference on Machine Learning, 6105–6114.

Touvron, H.; Cord, M.; Douze, M.; Massa, F.; Sablayrolles, A.; and Jégou, H. 2021. Training data-efficient image transformers & distillation through attention. In Proceedings of the International Conference on Machine Learning, 10347–10357.

Vaswani, A.; Shazeer, N.; Parmar, N.; Uszkoreit, J.; Jones, L.; Gomez, A. N.; Kaiser, L.; and Polosukhin, I. 2017. Attention is all you need. In Proceedings of the International Conference on Neural Information Processing Systems, 5998–6008.

Wang, G.; Yang, S.; Liu, H.; Wang, Z.; Yang, Y.; Wang, S.; Yu, G.; Zhou, E.; and Sun, J. 2020a. High-order information matters: Learning relation and topology for occluded person re-identification. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 6449–6458.

Wang, G.; Yang, S.; Liu, H.; Wang, Z.; Yang, Y.; Wang, S.; Yu, G.; Zhou, E.; and Sun, J. 2020b. High-order information matters: Learning relation and topology for occluded person re-identification. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 6449–6458.

Wang, G.; Yuan, Y.; Chen, X.; Li, J.; and Zhou, X. 2018. Learning discriminative features with multiple granularities for person re-identification. In Proceedings of the 26th ACM International Conference on Multimedia, 274–282.

Wei, L.; Zhang, S.; Gao, W.; and Tian, Q. 2018. Person transfer gan to bridge domain gap for person re-identification. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 79–88.
Wu, S.; Bai, Y.; Wang, C.; and Duan, L. 2021. Person retrieval with conv-transformer. In Proceedings of the IEEE International Conference on Multimedia and Expo, 1–6.

Xia, B. N.; Gong, Y.; Zhang, Y.; and Poellabauer, C. 2019. Second-order non-local attention networks for person re-identification. In Proceedings of the IEEE International Conference on Computer Vision, 3760–3769.

Xiao, T.; Li, Y.; Zhu, J.; Yu, Z.; and Liu, T. 2019. Sharing attention weights for fast transformer. In Proceedings of the International Joint Conference on Artificial Intelligence.

Xie, E.; Wang, W.; Yu, Z.; Anandkumar, A.; Alvarez, J. M.; and Luo, P. 2021. SegFormer: Simple and efficient design for semantic segmentation with transformers. arXiv preprint arXiv:2105.15203.

Yang, B.; Tu, Z.; Wong, D. F.; Meng, F.; Chao, L. S.; and Zhang, T. 2018. Modeling localness for self-attention networks. In Proceedings of the International Conference on Empirical Methods in Natural Language Processing, 4449–4458.

Yao, H.; Zhang, S.; Hong, R.; Zhang, Y.; Xu, C.; and Tian, Q. 2019. Deep representation learning with part loss for person re-identification. IEEE Transactions on Image Processing, 28(6): 2860–2871.

Yuan, L.; Chen, Y.; Wang, T.; Yu, W.; Shi, Y.; Jiang, Z.; Tay, F. E.; Feng, J.; and Yan, S. 2021. Tokens-to-token vit: Training vision transformers from scratch on imagenet. arXiv preprint arXiv:2101.11986.

Zhang, A.; Gao, Y.; Niu, Y.; Liu, W.; and Zhou, Y. 2021. Coarse-to-fine person re-identification With auxiliary-domain classification and second-order information bottleneck. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 598–607.

Zheng, L.; Huang, Y.; Lu, H.; and Yang, Y. 2019. Pose-invariant embedding for deep person re-identification. IEEE Transactions on Image Processing, 28(9): 4500–4509.

Zheng, L.; Shen, L.; Tian, L.; Wang, S.; Wang, J.; and Tian, Q. 2015. Scalable person re-identification: A benchmark. In Proceedings of the IEEE International Conference on Computer Vision, 1116–1124.

Zhou, J.; Lin, K.-Y.; Li, H.; and Zheng, W.-S. 2021. Graph-based high-order relation modeling for long-term action recognition. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 8984–8993.

Zhu, K.; Guo, H.; Liu, Z.; Tang, M.; and Wang, J. 2020a. Identity-guided human semantic parsing for person re-identification. In Proceedings of the European Conference on Computer Vision, 346–363.

Zhu, X.; Su, W.; Lu, L.; Li, B.; Wang, X.; and Dai, J. 2020b. Deformable detr: Deformable transformers for end-to-end object detection. arXiv preprint arXiv:2010.04159.

Zhuang, Z.; Wei, L.; Xie, L.; Zhang, T.; Zhang, H.; Wu, H.; Ai, H.; and Tian, Q. 2020. Rethinking the distribution gap of person re-identification with camera-based batch normalization. In Proceedings of the European Conference on Computer Vision, 140–157.