Progressive End-to-End Object Detection in Crowded Scenes

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Abstract

In this paper, we propose a new query-based detection framework for crowd detection. Previous query-based detectors suffer from two drawbacks: first, multiple predictions will be inferred for a single object, typically in crowded scenes; second, the performance saturates as the depth of the decoding stage increases. Benefiting from the nature of the one-to-one label assignment rule, we propose a progressive predicting method to address the above issues. Specifically, we first select accepted queries prone to generate true positive predictions, then refine the rest noisy queries according to the previously accepted predictions. Experiments show that our method can significantly boost the performance of query-based detectors in crowded scenes. Equipped with our approach, Sparse RCNN achieves 92.0% AP, 41.4% MR\(^{-2}\) and 83.2% JI on the challenging CrowdHuman [35] dataset, outperforming the box-based method MIP [8] that specifies in handling crowded scenarios. Moreover, the proposed method, robust to crowdedness, can still obtain consistent improvements on moderately and slightly crowded datasets like CityPersons [47] and COCO [26]. Code will be made publicly available at https://github.com/megvii-model/Iter-E2EDET.

1. Introduction

Crowded object detection is a practical yet challenging research field in computer vision. Many research efforts have been made and achieved impressive progress [28, 5, 6, 46, 49, 8, 33, 14, 23] in the last few decades. However, most of them [28, 5, 6, 46, 49, 8, 33, 14] require hand-craft components, e.g. anchor settings and post-processing, resulted in sub-optimal performance in handling scenes.

Recently, Carion et al. [3] proposed a fully end-to-end object detection framework DETR, which introduces learnable queries to represent objects and achieves competitive performance without any post-processing. It can be categorized as a query-based approach to differentiate from the box-based [25, 24, 48] and point-based [39, 44] methods. Following DETR [3], Sparse RCNN [37] ensures object queries interact with local feature of Region of Interest (RoI), while deformable DETR [52] proposes attention modules that only attend to a small set of key sampling points. They further improve the detection accuracy and mitigate several issues occurred in DETR: slow conver-
ence and high computational overhead.

The above success inspires us to study query-based object detection methods in crowded scenes, aiming at designing a more sophisticated end-to-end detection framework. Although these query-based approaches [18, 52] can obtain significant results on the slightly crowded datasets like COCO [26], our initial studies show they suffer from several unresolved challenges in crowded scenes: (1) the query-based detector tends to infer multiple predictions for a single object, with false positives introduced. Figure 1a shows a common failure case; (2) The performance of a query-based detector becomes saturated or even worse as the depth of decoding stage increases, which is depicted in the Appendix.

**Our motivations.** Further investigations on the query-based method, Sparse RCNN [37], yield the following intriguing findings in crowd scenes. As described in Figure 2a, a large percentage of target objects can be accurately predicted by those predictions with high confidence scores (e.g., higher than a threshold of 0.7), while containing few false positives. These predictions are more likely to be true positives that can be taken as accepted predictions. While the rest, where a considerable number of true positives and false positives exist, can be regarded as noisy predictions. Naturally, if an object is detected by one accepted prediction, there is no need for noisy predictions to detect it again. Hence, Why not strengthen the discrimination of those noisy predictions given the context of the accepted predictions? To this end, the noisy queries can ‘perceive’ whether their targets have been detected or not. If so, their confidence scores will be reduced and then filtered out.

**Our contributions** Motivated by this, we propose a progressive prediction method equipped with a prediction selector, relation information extractor, query updater, and label assignment to improve the performance of query-based object detectors in handling crowded scenes.

First, we develop a prediction selector to select queries associated with high confidence scores as accepted queries, leaving the rest as noisy queries. Then, to let the noisy queries ‘perceive’ whether their targets have been detected or not, we design a relation extractor for relation modeling between noisy queries and their accepted neighbors. Further, a query updater is developed by performing a new local self-attention attending to spatially-related neighbors only. Finally, a new one-to-one label assignment rule is introduced to assign samples among the accepted and refined noisy queries step by step. With the proposed method, the above problems can be well addressed: (1) Each object can be detected only once, which greatly decreases the number of false positives while increasing the number of true positives, as described in Figure 1b; (2) As depicted in Figure 2b, the performance is consistently improved compared with its counterparts [37, 52] that have the same depth of decoding stage.

Our method is generic and can be incorporated into multiple architectures [37, 52], and delivers significant performance improvements of query-based detectors. Equipped with our approach, Sparse RCNN [37] with ResNet-50 [16] backbone obtains 92.0% AP, 41.4% MR−2 and 83.2% JI on the challenging dataset CrowdHuman [35], outperforming the box-based method MIP [8]. Besides, deformable DETR [52], equipped with our approach, also achieves 92.1% AP and 84.0% JI. Moreover, our approach works reasonably well for less crowded scenes, e.g., the Sparse RCNN with our approach can still obtain 1.0% MR−2 and 1.1% AP gains on moderately and slightly crowded datasets Citypersons [47] and COCO [26], respectively.

**2. Related works**

**End-to-end object detection.** RelationNet [20] is one of the pioneering works trying to predict results directly, achieving promising performance compared to their counterparts on several famous benchmarks. DETR [3] introduces learnable queries to represent objects and perform single prediction for each instance directly. Subsequently, deformable-DETR [52] limits the attention field of each query to a local area around the reference points to accelerate the convergence and improve detection performance. Meanwhile, Sparse R-CNN [37] utilizes a fixed set of learnable queries to formulate objects instead of a number of proxy representation, e.g., anchors. Analogous to deformable DETR, RoIAlign [15] is applied to limit the attention field in a local region. Adaptive Clustering Transformer [51] proposes to improve the attention distribution in DETR’s encoder by LSH approximate clustering for convergence acceleration. UP-DETR [9] designs a new self-supervised method to improve the convergence speed of DETR, while TSP[38] analyzes the main factors contributing to slow convergence in DETR. SMCA [13] explores a better information interaction mechanism to further accelerate convergence and improve the performance of DETR.

**Object detection in crowded scenes.** Research community has poured much interest in exploring occlusion problems on pedestrian detection. Specific methods have been proposed to mitigate this problem, including detecting by parts [28, 5, 6, 46, 49] and improving hand-crafted rules in training target design. Recently, CNN-based methods have dominated the crowded object detection and achieved considerable gains. Several works propose new loss functions to address problems of crowded detection [45, 49]. Besides, the effectiveness of NMS is based on the assumption that multiple instances rarely occur at the same location in an image, which is not true in crowded scenes. But designing duplicate removal for crowded scenes is non-trivial. Soft-NMS [1] and Softer-NMS [17] replace hard removal of nearby proposals with score decay. Several works propose to use a neural network to simulate the function of NMS for
duplicates removal [18, 32]. Others explore NMS-aware training, including NMS with adaptive threshold [19, 27], feature embedding [34] and multiple prediction with set suppression [8, 21], to tackle problem of object detection in crowded scenes. 

Recently, PEDR [23] proposes several techniques to improve the performance of query-based detectors in coping with crowded detection, which is orthogonal to ours. Their techniques are also applicable to our work.

Relation modeling for object detection. As discussed in [20], early works [10, 12, 41, 42, 30] use object relations as a post-processing step. The detected objects are re-scored by considering object relationships. For example, co-occurrence, which indicates how likely two object classes can exist in the same image, is used by DPM [11] to refine object scores. The subsequent approaches [31, 7] try more complex relation models, by taking additional positions and size into account. These methods achieve moderate success in the pre-deep learning era but do not prove the effectiveness in CNNs. Several recent works perform spatial reasoning [22, 36, 4, 18] to model object relations. Among them, GossipNet [18] and RelationNet [20] are the representative methods. Both share the same spirit of modeling relations among boxes. However, the network of GossipNet [18] is complex (depth>80) and its computation cost is demanding. Although it allows end-to-end learning in principle, no experimental evidence approves. RelationNet [20] utilized the self-attention for feature interaction and obtained a promising improvement in general object detection. Nevertheless, it doesn’t show a promising performance in dealing with crowd scenes [35].

Recent works related to ours are PS-RCNN [14] and IterDet [33]. They proposed to detect objects according to the previous predicted ones. They need to mask the feature [14] or produce a history map [33] to memorize the previous detections, introducing noise while limiting performance improvement [14] or incur heavy computation [33]. Even so, both of them need a post-processing method to remove duplicates in every iteration.

Recent query-based object detectors [37, 52, 51, 9, 38, 13] utilized learnable queries to represent objects, and take advantage of the self/cross-attention to model the relations among queries, detecting objects in an end-to-end manner. Our work inherits the methodology and boosts their performance in heavily, moderately, and slightly crowded scenes.

3. Methodology

In this section, we first revisit the query-based object detector, e.g. Sparse RCNN [37] briefly. Next, we illustrate our approach primarily deployed on Sparse RCNN explicitly. Finally, the main differences of detector design will be discussed as follows.

3.1. Query Based Object Detector

Our approach can be deployed on most query-based object detectors [3, 37, 52]. To illustrate the proposed method, we choose Sparse RCNN [37] as our default instantiation. Figure. 4a depicts its object detection pipeline, which can also be formulated as:

\[
\begin{align*}
    x_{t-1} &\leftarrow \mathcal{P}^{box}(x_{FPN}^{t}, b_{t-1}), \\
    q^*_{t-1} &\leftarrow \text{MSA}_{t-1}(q_{t-1}), \\
    q_t &\leftarrow \text{DynConv}_{t-1}(q^*_{t-1}, x_{t-1}), \\
    b_t &\leftarrow \mathcal{B}_{t-1}(q_t),
\end{align*}
\]

where \( q \in \mathbb{R}^{\text{N} \times d} \) denotes the learnable object query. \( N \) and \( d \) denote the number and dimension of query \( q \), respectively. At stage \( t \), an RoIAlign [15] \( \mathcal{P}^{box} \) extracts RoI features from FPN features \( x_{FPN} \), under the guidance of bounding box \( b_{t-1} \) predicted by the previous stage. Meanwhile, a multi-head self-attention module \( \text{MSA}_{t-1} \) is applied to the input query \( q_{t-1} \) to get the transformed query \( q^*_{t-1} \). Then, a dynamic convolution module \( \text{DynConv}_{t-1} \) takes both \( x_{t-1} \) and \( q^*_{t-1} \) as inputs and performs dynamic convolution to generates \( q_t \) for the next stage. Simultaneously, \( q_t \) is fed into the box prediction branch \( \mathcal{B}_{t-1} \) for current bounding box prediction \( b_t \), which is the input of the next stage \( t \).

3.2. Our Method

As illustrated in Figure. 3, the proposed progressive predicting method consists of several components: prediction selector, relation information extractor, query updater, and label assignment, which will be introduced in detail next.

Prediction selector. For the findings described in Sec. 1, a prediction selector is developed to select those queries prone to generating predictions with high confidence scores as accepted queries, while leaving the rest as noisy ones that need to be further refined. This procedure can be formulated in Equ.(2).

\[
\begin{align*}
    \mathcal{D}_{t-1}^h &\leftarrow \{ b_i | s_i \geq s \land b_i \in \mathcal{D}_{t-1} \}, \\
    \mathcal{D}_{t-1}^l &\leftarrow \mathcal{D}_{t-1} \setminus \mathcal{D}_{t-1}^h.
\end{align*}
\]

where \( t \) is the stage number. \( \mathcal{D}_{t-1} \) denote the whole predictions produced by the whole queries in the previous \( t-1 \) stage. \( \mathcal{D}_{t-1}^h \) and \( \mathcal{D}_{t-1}^l \) indicate the accepted predictions and noisy predictions generated from the accepted and noisy queries, respectively. \( b_i \) and \( s_i \) denote the predicted box and its confidence score, respectively. \( s \) is the confidence score threshold.

Relation information extractor. As mentioned in Sec. 1, a large percentage of target objects can be accurately predicted by the accepted queries. Therefore, if an object is detected by one accepted prediction, there is no need for
noisy predictions to detect it again. In order to equip these noisy queries with the capability of perceiving whether their targets have been detected or not, we develop a relation information extractor to model the relation between the noisy predictions and their accepted neighbors.

The detailed design of the relation information extractor is illustrated in Figure 5, with the procedure formulated in Equ.(3) as well. For each noisy prediction \( b_i \), we first find their accepted neighbors \( N(b_i) \) in \( D^h_{t-1} \), constructing the spatially-related pairs \((b_i, N(b_i))\). Then, the encoded pairs together with the intersection-over-union (IoU) between them are fed to a compact network to obtain the geometry relation features \( H(b_i) \). Since the number of accepted neighbors corresponding to each noisy prediction is uncertain. An aggregation function is employed to reduce \( H(b_i) \) to the same feature dimension, while maintaining the permutation-invariance property. In our approach, we use max pooling by default. Besides, the pooled geometry features, fused with the transformed query features, are further activated by a non-linear function.

\[
N(b_i) \leftarrow \{ b_j | O(b_i, b_j) \geq \theta, b_j \in D^h_{t-1}, b_j \in D^h_{t-1} \}, \quad H(b_i) \leftarrow U(E(b_i, N(b_i))), \quad b_i \in D^h_{t-1}, \quad R(b_i) \leftarrow T \left( \text{MaxPool}(H(b_i)) + F(q_i) \right). \tag{3}
\]

where \( N(\cdot) \) represents a function that finds neighbors for a box \( b_i \) based on the IoU \( O(\cdot, \cdot) \) with a threshold \( \theta \). Here, we use it to find the accepted neighbors in \( D^h_{t-1} \) for the noisy predictions in \( D^d_{t-1} \). \( E(\cdot, \cdot) \) refers to the sine and cosine spatial positional encoding function which is the same as that [20, 43]. Also, \( U(\cdot, \cdot) \) refers to a function used to generate geometry relation features \( H(b_i) \) from the encoded inputs. The noisy query \( q_i \) corresponds to noisy prediction \( b_i \) in \( D^d_{t-1} \), transformed by the function \( F(\cdot) \). The pooled geometry features and transformed query features \( F(q_i) \) are fused through element-wise summation, followed by a function \( T \) to produce the desired relation features \( R(b_i) \).

As depicted in Figure 5, \( U(\cdot, \cdot) \) consists of two consecutive fc layers with ReLU [29] activation to increase the non-linearity. Note that \( F(\cdot) \) and \( U(\cdot, \cdot) \) share the same architecture, but are weight-independent. Here, the gradients of \( q_i \) are stopped from back-propagating to the previous stages.

**Query updater.** To further refine the features of noisy queries, a query updater is developed, which is formulated in Equ.(4). Since the data distribution of \( D^d_{t-1} \) and \( D^h_{t-1} \) is different from that of \( D^d_{t-1} \), a new set of learnable queries is first introduced to complement the relation features through element-wise summation. Then the set of complemented noisy queries is taken as the input query \( q_{t-1} \) to perform a new local self-attention LMSA\(_{t-1}\) and the subsequent dynamic convolution given in Equ.(1).

\[
q_{t-1} \leftarrow \{ q_i, q_i = R(b_i) + e_i \}, \quad b_i \in D^d_{t-1}, e_i \in E \\
q^*_i \leftarrow \text{LMSA}_{t-1}(q_{t-1}). \tag{4}
\]
Generally, our approach can be deployed on most query-based object detectors [3, 37, 52]. To illustrate the proposed method, we choose Sparse RCNN [37] as our default instantiation. It consists of $t (t = 0$ by default) decoding stages, each of which performs prediction according to Equ. (1). As described in Figure. 3, we keep the first $t - 1$ decoding stages unchanged and only equip the last stage with the proposed method. Therefore, main differences lie in the last decoding stage, which will be described in the following.

**Algorithm 1** Label Assignment for $D^l_t$.

\[
\begin{align*}
\text{Input:} & \quad D^l_t, D^h_t, G; \\
1: & \quad D^l_t: \text{results of } D^l_{t-1} \text{ in Equ.(2) from stage } t; \\
2: & \quad D^h_t: \text{results of } D^h_{t-1} \text{ in Equ.(2) from stage } t; \\
3: & \quad G: \text{target boxes.} \\
\text{Output:} & \quad \text{The matched predictions } M^l_D \text{ and corresponding targets } M^l_l \text{ after assignment.} \\
4: & \quad \text{Compute matching costs } C^l_t \text{ between } D^l_t \text{ and } G; \\
5: & \quad M^l_G, M^h = \text{HungarianMatch}(D^h_t, G, C^l_t); \\
6: & \quad G^l_t = G - M^l_G; \\
7: & \quad \text{Compute matching costs } C^h_t \text{ between } D^l_l \text{ and } G^l_t; \\
8: & \quad M^l_G, M^l_D = \text{HungarianMatch}(D^l_t, G^l_t, C^h_t); \\
9: & \quad \text{return } M^l_G, M^l_D; \\
\end{align*}
\]

Since object detection mainly focuses on the local region in an image. We design a new local self-attention module LMSA$_{l}$ to update the noisy query $q_{t-1}$. It ensures each query only interacts with local neighbors instead of the whole queries over the full image. The local self-attention first finds those neighbors of each query based on the boxes’ IoUs whose values are greater than 0. Then it performs the ‘qkv’ mechanism in the same way as MSA. To this end, we perform self-attention locally instead of globally.

Different from the neighbor finding rule in [23], we adopt the function $\mathcal{N}(\cdot)$ to select neighbors from $D_{t-1}$ that are spatially related to $q_{t-1}$ in terms of IoU. Note that, the new local self-attention LMSA$_{l}$ is used to replace the MSA$_{l-1}$ in Equ.(1) for feature interaction.

**Label assignment** Since accepted queries tend to generate true positive predictions, while the noisy ones involve a considerable number of true positives and false positives. Towards end-to-end object detection, we introduce a new one-to-one label assignment rule to assign samples step by step. Specifically, we first match the accepted predictions $D^l_{t-1}$ with the ground truth set of objects. Then remove those targets that have been matched, and mainly consider the bipartite matching between noisy predictions $D^h_{t-1}$ and the remaining ground truth set of objects. This matching process is described in Algorithm 1, where the matching cost computation is slightly different from the original version [37]. A spatial prior is adopted to compute the matching cost $C$, that is, the center of bounding box $b_t$ needs to fall in the corresponding target box. Except for it, the formulation of the matching cost function is identical to the original work.

### 3.3. Difference of Detector Design

Generally, our approach can be deployed on most query-based object detectors [3, 37, 52]. To illustrate the proposed...
standard ResNet-50 [16] pre-trained on ImageNet as backbone. We train our model with the Adam optimizer with a momentum of 0.9 and weight decay of 0.0001. Models are trained for 50, 000 iterations. The initial learning rate is 0.00005 and reduced by a factor of 0.1 at iteration 37,500. The last stage joins the optimization after 5,000 iterations of training. \( \lambda_{cls} = 2, \lambda_{l1} = 5, \lambda_{giou} = 2 \). The default number of proposal boxes, proposal features, and stages are set to 500, 500, and 6, respectively. Additionally, The dimension of intermediate features in relationship extractor \( R \) is 256. The gradients are detached at proposal boxes from the second stage to stabilize training. Besides, those negative samples, whose intersection-over-area (IoA) between any ignore region is higher than a threshold of 0.7, are not involved in training. Further, the hyper-parameters \( s \) and \( \theta \) are 0.7 and 0.4 by default in different query-based detectors [37, 52].

### 4.1. Experiments on CrowdHuman

CrowdHuman [35] contains 15,000, 4,370 and 5,000 images for training, validation and test, respectively. For a fair comparison, we re-implement most of the involved models [24, 21, 25, 27, 48, 8, 40, 44, 3, 52, 37, 23, 18, 20]. Results are evaluated on the validation set, using the full-body annotations in the dataset.

#### Main results.

We compare with mainstream object detectors, including box-based: one-stage [25, 48], two-stages [8, 24, 21, 27], and point-based [40, 44] as well as query-based [3, 52, 37, 23].

As shown in Table 2, our approach outperforms these well-established detectors, achieving significant performance improvements over the box-based, point-based, and query-based counterparts, illustrating the effectiveness of our approach in handling crowded scenes. Specifically, our method achieves 1.8% AP and 0.9% JI gains over the state-of-the-art box-based approach MIP [8], which specializes in coping with crowded scenes.

The query-based method Sparse RCNN [37], equipped with the proposed method and 500 queries, can achieve 92.0% AP, 41.4% MR and 83.2% JI on the challenging CrowdHuman dataset [35], which is 1.3%, 3.3% and 1.8% better than its counterpart – original Sparse RCNN [37].

When increasing the number of queries to 750, our approach can still obtain a better performance of 92.5% AP and 83.3% JI. This is because more queries can cover more patterns of objects in the image, such as scale, size, position, and other characteristics. Additionally, equipped with our approach, deformable DETR [52]2 can also obtain 2.2% MR improvements over the original deformable DETR [52]. Moreover, It also achieves 1.4% AP and 1.6% JI gains over the box-based method MIP [8], demonstrating the effectiveness of our approach.

| Method          | #Queries | AP   | MR\(^{-2}\) | JI  |
|-----------------|----------|------|-------------|-----|
| box-based       |          |      |             |     |
| RetinaNet [25]  | -        | 85.3 | 55.1        | 73.7|
| ATSS [48]       | -        | 87.0 | 51.1        | 75.9|
| ATSS [48]+MIP [8]| -        | 88.7 | 51.6        | 77.0|
| FPN [24]+NMS    | -        | 85.8 | 42.9        | 79.8|
| FPN [24]+soft NMS | -    | 88.2 | 42.9        | 79.8|
| FPN+MIP [8]     | -        | 90.7 | 41.4        | 82.4|
| FPN+MNS         | -        | 84.9 | 46.3        |    |
| Adaptive NMS\(^{†}\) [27] | -    | 84.7 | 47.7        |    |
| PBN\(^{†}\) [21] | -        | 89.3 | 43.4        |    |
| point-based     |          |      |             |     |
| FCOS [40]       | -        | 86.8 | 54.0        | 75.7|
| FCOS [40]+MIP [8]| -        | 87.3 | 51.2        | 77.3|
| POTO [44]       | -        | 89.1 | 47.8        | 79.3|
| query-based     |          |      |             |     |
| DETR [3]        | 100      | 75.9 | 73.2        | 74.4|
| PEDR [23]       | 1000     | 91.6 | 43.7        | 83.3|
| D-DETR [52]     | 1000     | 91.5 | 43.7        | 83.1|
| S-RCNN [37]     | 500      | 90.7 | 44.7        | 81.4|
| S-RCNN [37]     | 750      | 91.3 | 44.8        | 81.3|
| S-RCNN+Ours     | 500      | 92.0 | 41.4        | 83.2|
| S-RCNN+Ours     | 750      | 92.5 | 41.6        | 83.3|
| D-DETR+Ours     | 1000     | 92.1 | 41.5        | 84.0|

Table 2: Comparisons of different methods on CrowdHuman validation set, +MIP represents multiple instance prediction with set NMS as post-processing. \(^{†}\) indicates the approach is implemented by PBM [21]. S-RCNN – Sparse RCNN [37]. D-DETR – deformable DETR [52].

### Ablation study of different modules.

To explore the effectiveness of the proposed modules in Sec. 3.2, we conduct extensive ablation study of the relation information extractor \( R \), local self-attention module LMSA and the newly initialized embedding \( E \). All experiments are conducted on Sparse RCNN [37] with 500 queries, ResNet-50 [16] backbone and evaluated on CrowdHuman dataset. Table 3a shows that the relation information extractor \( R \) can obtain an improvement of 0.8% AP, 1.7% MR and 1.6% JI. It indicates its effectiveness in reducing false positives and recalling false negatives. Moreover, when equipped

| Method          | #Queries | AP   | MR\(^{-2}\) | JI  |
|-----------------|----------|------|-------------|-----|
| box-based       |          |      |             |     |
| RetinaNet [25]  | -        | 85.3 | 55.1        | 73.7|
| ATSS [48]       | -        | 87.0 | 51.1        | 75.9|
| ATSS [48]+MIP [8]| -        | 88.7 | 51.6        | 77.0|
| FPN [24]+NMS    | -        | 85.8 | 42.9        | 79.8|
| FPN [24]+soft NMS | -    | 88.2 | 42.9        | 79.8|
| FPN+MIP [8]     | -        | 90.7 | 41.4        | 82.4|
| FPN+MNS         | -        | 84.9 | 46.3        |    |
| Adaptive NMS\(^{†}\) [27] | -    | 84.7 | 47.7        |    |
| PBN\(^{†}\) [21] | -        | 89.3 | 43.4        |    |
| point-based     |          |      |             |     |
| FCOS [40]       | -        | 86.8 | 54.0        | 75.7|
| FCOS [40]+MIP [8]| -        | 87.3 | 51.2        | 77.3|
| POTO [44]       | -        | 89.1 | 47.8        | 79.3|
| query-based     |          |      |             |     |
| DETR [3]        | 100      | 75.9 | 73.2        | 74.4|
| PEDR [23]       | 1000     | 91.6 | 43.7        | 83.3|
| D-DETR [52]     | 1000     | 91.5 | 43.7        | 83.1|
| S-RCNN [37]     | 500      | 90.7 | 44.7        | 81.4|
| S-RCNN [37]     | 750      | 91.3 | 44.8        | 81.3|
| S-RCNN+Ours     | 500      | 92.0 | 41.4        | 83.2|
| S-RCNN+Ours     | 750      | 92.5 | 41.6        | 83.3|
| D-DETR+Ours     | 1000     | 92.1 | 41.5        | 84.0|

2The detail implementation of deformable DETR with the proposed schema is illustrated in the Appendix.
with the new local self-attention LMSA, the performance on three evaluation metrics is further boosted, since the local self-attention can reduce duplicates effectively. Further, the newly initialized embeddings, aiming to approximate the new data distribution of noise predictions, can slightly improve MR−2.

Ablation study of hyper-parameter $s$. To analyze the effect of the confidence score threshold $s$, we first formulate the relation between detection boxes and target boxes in an image as a bipartite graph $G = (V, E)$. It consists of a set $V = D \cup G$ and nodes $E$. $D$ represents a set of predicted boxes whose scores are higher than the pre-defined score threshold, while $G$ denotes the target boxes. An edge in $E$ is defined as overlapping when the $IoU$ value, between a box in $D$ and the other one from $G$, is higher than $0.5$ by default$^3$. Hence, the matching results can be acquired after applying the Hungarian Algorithm. As shown in Figure. 2, as the confidence score increases, the number of true positives shows a clean upward trend while the number of false positives decreases rapidly. Also, Figure. 7a depicts the performance our method can achieve under different values of $s$, where the performance increases slightly as $s$ increases. Thus, if not specific, we set $s$ to $0.7$ by default.

Ablation study of hyper-parameter $\theta$. Here, we analyze the effect of the hyper-parameter intersection-over-union threshold $\theta$. As discussed in Sec. 1, making sure a box candidate can ‘perceive’ its neighbors helps a noisy query decide to decrease its confidence score or not, which is also the prerequisite for our method to work effectively. Different settings of intersection-over-union (IoU) threshold $\theta$ may affect the performance of the whole detector. We perform experiments on the CrowdHuman dataset [35] with $s$ frozen as 0.7 while changing the value of $\theta$ linearly. From Figure. 7b, we found our approach is robust to the change of $IoU$ threshold. This success may attribute to the good approximating feature of the newly designed components.

Comparison with previous relation modeling works. To differentiate the previous works and ours, we evaluate the following the same training setting in [18, 20, 24]. All models use FPN [24] with ResNet-50 [16] as backbone, following the same training setting in [18, 20, 24].

As shown in Table. 3b, our approach shows better performance when compared with previous relation modeling works. Surprisingly, both RelationNet [20] and GossipNet [18] suffer from a significant drop in AP and MR−2. It could attribute to the sub-optimal label assignment rule. Since both of them choose the prediction with the highest confidence score around one target as the correct box and take the rest as negatives. The predicted coordinates are not involved in computing loss, which might lead to the performance degradation in crowded scenes.

Analysis on false positives. To understand the factors contributing to the performance improvement, we conduct an error analysis on our method. We adopt the recently proposed TIDE [2] to compare our approach with the counterpart Sparse RCNN [37]. We analyzed the composite error at Recall=0.9 for all methods. As illustrated in Figure. 6, our method performs better at removing duplication, providing more accurate localization, and reducing mistaken recognition. Since part of queries can perceive whether their targets are detected or not through the relation information extractor. Also, the local self-attention module ensures queries only interact with their neighbors rather than the whole. To this end, the duplicates could be eliminated efficiently. Besides, with identity mapping plugged in the last regression branch for box prediction, the number of training samples in the previous decoding stage increases, making the optimization much easier. Additionally, benefiting from the new learnable embeddings for data distribution approximation, the representation ability of object queries are further enhanced.

4.2. Experiments on Citypersons

CityPersons [47] is one of the widely used benchmarks for pedestrian detection. It contains 5,000 images (2,975 for training, 500 for validation, and 1,525 for testing, respectively). Each image has a size of 1024 × 2048. To improve the overall performance, we proposed to pre-train all models on the CrowdHuman dataset and fine-tune them on CityPersons (reasonable) training subset, then tested on the (reasonable) validation subset. For those box-based methods, we train and evaluate them with the image resolution enlarged by 1.3 × compared to the original one for better accuracy. The query-based approaches are trained and evaluated at the original image size with 500 queries. The other settings remain the same as those of Sparse RCNN [37] and deformable DETR [52].

4.3. Experiments on COCO.

According to Table 1, the crowdness of COCO [26] is very low, which is beyond our design purpose. Nevertheless, we still conduct an experiment on this dataset to verify: 1) whether our method generalizes well to multi-class detection; 2) whether our approach can still handle slightly crowded scenarios, especially with isolated instances.
Following the common practice of Sparse RCNN [37] with 500 queries, we use a subset of 5000 images in the original validation set (named minival) for validation while using the remaining images in the training and validation set for training. Except for the proposed modules and label assignment rule in the last stage, other settings remain the same as the original methods [52, 37]. Table 4 shows the performance comparisons with deformable DETR [52] and Sparse RCNN [37]. Moderate improvements are obtained, e.g. 0.9% AP higher than the deformable DETR [52] and 1.1% AP higher than the Sparse RCNN [37]. The experimental results reflect the effectiveness of our progressive predicting approach in slightly crowded scenarios, proving the proposed method can also solve the performance saturation problem of query-based detectors.

5. Conclusion

In this paper, we propose a progressive prediction method to boost the performance of query-based object detectors in handling crowded scenes. Equipped with our approach, two representatives query-based methods, Sparse RCNN [37] and deformable DETR [52] achieve consistent improvements over the heavily, moderately, as well as slightly crowded datasets [35, 47, 26], which suggests our approach is robust to crowdedness. Since Sparse RCNN [37] and deformable DETR [52] require large computing resources, making it difficult for our method to be deployed on devices with limited computing capacity. How to develop a computation-efficacy end-to-end detector is still under exploration. Besides, we found the decision boundary for the noisy queries is unclear. We believe that the performance can be further improved if a better feature engineering method or loss function is adopted. However, it is beyond the purpose of this work.
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