GROUP DETR: FAST TRAINING CONVERGENCE WITH DECOUPLED ONE-TO-MANY LABEL ASSIGNMENT

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\textbf{ABSTRACT}

Detection Transformer (DETR) relies on One-to-One label assignment, i.e., assigning one ground-truth (gt) object to only one positive object query, for end-to-end object detection and lacks the capability of exploiting multiple positive queries. We present a novel DETR training approach, named Group DETR, to support multiple positive queries. To be specific, we decouple the positives into multiple independent groups and keep only one positive per gt object in each group. We make simple modifications during training: (i) adopt $K$ groups of object queries; (ii) conduct decoder self-attention on each group of object queries with the same parameters; (iii) perform One-to-One label assignment for each group, leading to $K$ positive object queries for each gt object. In inference, we only use one group of object queries, making no modifications to both architecture and processes. We validate the effectiveness of the proposed approach on DETR variants, including Conditional DETR, DAB-DETR, DN-DETR, and DINO.

\section{Introduction}

In object detection, label assignment is a crucial and classic topic. It defines positive and negative samples for detector training (Zhang et al., 2020), which affects model learning and impacts detection performance. Many label assignment methods (Cao et al., 2020; Zhang et al., 2020; Kim & Lee, 2020; Zhu et al., 2020a; Ge et al., 2021) are proposed to achieve significant improvements over various detectors (Ren et al., 2015a; He et al., 2017; Lin et al., 2017; Tian et al., 2019). They can be categorized into two main types based on the number of matched positives per gt object: (1) One-to-Many assignment: each gt object can be assigned to multiple positive samples, and (2) One-to-One assignment: one gt object can only be assigned to exactly one positive sample.

Among them, One-to-Many assignment is widely adopted in modern detectors (Ren et al., 2015a; He et al., 2017; Lin et al., 2017; Tian et al., 2019; Chen et al., 2021), achieving dominant performances and enabling fast training convergences. One undesired effect of One-to-Many assignment is that it produces duplicate predictions, preventing the removal of post-processing steps such as non-maximum suppression (NMS) (Hosang et al., 2017). DETR (Carion et al., 2020) breaks this convention and achieves end-to-end training by introducing object queries, applying transformer layers (Vaswani et al., 2017), and adopting One-to-One assignment (Kuhn, 1955). But it suffers from the slow convergence issue. Previous attempts (Zhu et al., 2019; Meng et al., 2021; Chen et al., 2022; Liu et al., 2022) alleviate this issue from the perspective of attention module design in transformer layers. Although a $10 \times$ speed up (from 500 epochs to 50 epochs) is achieved, DETR-based methods still produce unpleasant results with a standard $1 \times$ training schedule (12 epochs). In this paper, we attribute these results to One-to-One assignment\textsuperscript{*} and provide a further speed up on training convergence by exploring label assignment methods on DETR-based detectors.

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\textsuperscript{1}The reasons are three folds: (1) detectors (Lin et al., 2017; Tian et al., 2019; Chen et al., 2021) with One-to-Many assignment usually converge fast; (2) DETR-based methods (Carion et al., 2020) (with One-to-One assignment) suffer from slow convergence issue; (3) other end-to-end detectors (Wang et al., 2021; Sun et al.)
To investigate how label assignment methods affect the training convergence, we conduct experiments on Conditional DETR (Meng et al., 2021) with a $1 \times$ schedule. We gradually increase the number of total queries and matched positive queries per gt object. According to the experimental results in Figure 1, detection performance improves significantly with the increment of total queries and matched positive queries, while we can only obtain minor gains when only increasing the number of total queries. The above evidence suggests that multiple positive queries are key factors to fast training convergence. Despite multiple positive queries (One-to-Many assignment) producing higher performance, they bring duplicate predictions, making NMS necessary for post-processing. Given that One-to-One assignment is a crucial factor in achieving end-to-end training on object detection (Wang et al., 2021a; Sun et al., 2021a;b), we show a simple way to combine the merits of these two assignment methods.

In this paper, we propose Group DETR to support multiple positive queries in an end-to-end manner. To avoid duplicate predictions, Group DETR uses Decoupled One-to-Many assignment, which matches multiple positive queries per gt object (One-to-Many) in general but decouples them into multiple independent groups and keeps only one positive per object (One-to-One) in each group. To achieve it, we make simple modifications during training: (i) adopt $K$ groups of object queries; (ii) conduct decoder self-attention on each group of object queries with the same parameters; (iii) perform One-to-One assignment for each group, leading to $K$ positive object queries for each gt object. The design achieves fast training convergence, removes duplicate predictions, and enables end-to-end training. Moreover, we only use one group of queries in inference and do not modify both architecture and processes, bringing no extra cost compared with the original model.

Group DETR is a general training method that can be applied to various DETR-based models. Extensive experiments on MS COCO (Lin et al., 2014) prove that our method is effective in achieving fast training convergence. With a $1 \times$ training schedule, Group DETR gives a $5.0 \text{ mAP}/4.4 \text{ mAP}/1.5 \text{ mAP}/1.7 \text{ mAP}/1.0 \text{ mAP}$ gains on Conditional DETR (Meng et al., 2021)/DAB-DETR (Liu et al., 2022)/DAB-Deformable-DETR (Zhu et al., 2019)/Dino (Zhang et al., 2022). The non-trivial improvements hold when we adopt longer training schedules (e.g., 50 epochs). Label assignment methods are widely discussed in previous dense detectors (Lin et al., 2017; Tian et al., 2019; Chen et al., 2021) but few in DETR-based methods (Carion et al., 2020; Zhu et al., 2019; Meng et al., 2021). We hope our Decoupled One-to-Many assignment will motivate researchers to explore more in this direction.

Figure 1: Experimental results with Conditional-DETR-C5 on MS COCO. We show the results with One-to-One, One-to-Many, and ours Decoupled One-to-Many assignment. Increasing the number of queries does not significantly affect the capability of end-to-end training with the One-to-One assignment. When we adopt the One-to-Many assignment, the detection performance improves with the help of NMS but quickly falls to a very low level ($< 10 \text{ mAP}$) without NMS. Decoupled One-to-Many assignment enjoys the merits of both One-to-One and One-to-Many assignment. In the figure, the $x$-axis shows the number of object queries and the $y$-axis presents the detection performance (mAP).
2 RELATED WORKS

Label Assignment in Object Detection. Assignment between the gt objects and training samples is a crucial and classic topic in object detection (Redmon et al., 2016; Ren et al., 2015b; He et al., 2017; Lin et al., 2017). Anchor-based detectors (Liu et al., 2016; Lin et al., 2017) rely on the Intersection-over-Union (IoU) between anchors and gt boxes to select positive and negative samples. When the maximum IoU between an anchor and all gt boxes exceeds the hand-craft IoU threshold, the anchor will be matched to the maximum IoU gt box. Anchor-free detectors (Tian et al., 2019; Zhang et al., 2020) consider spatial and scale constraints when setting the points as positives or negatives. In ATSS (Zhang et al., 2020), the authors provide evidence that the applied assignment methods cause the differences in performance between anchor-based and anchor-free detectors during training. Its followers (Kim & Lee, 2020; Zhu et al., 2020a; Ge et al., 2021) further explore this direction and bring considerable improvements to object detection. The above methods can be divided into One-to-Many assignment, which needs NMS for post-processing. DETR Carion et al. (2020) explores an alternative way and achieves end-to-end training, removing the need for NMS. Recent studies (Wang et al., 2021a; Sun et al., 2021a) show that One-to-One assignment is the key factor in achieving end-to-end training. They provide evidence to make previous detectors to be end-to-end with One-to-One assignment. In this paper, we also focus on the assignment methods but on DETR-based methods, which are less studied in previous works.

Accelerating DETR Training. Since DETR Carion et al. (2020) was proposed, its slow convergence issue has been a critical problem many researchers try to address. Several works Meng et al. (2021); Zhu et al. (2020b); Gao et al. (2021); Wang et al. (2021b); Sun et al. (2021c) achieve 10× speed up for DETR. They mainly focus on proposing better cross-attention modules, designing new types of object queries, and updating methods for predicting boxes. Recently, DN-DETR Li et al. (2022) and DINO Zhang et al. (2022) attribute the slow convergence issue to the instability of hungarian matching. They propose query denoising and contrastive query denoising to speed up the model training further and achieve plausible results with only 1× training schedule. Different from previous methods, this paper aims to support one-to-many assignment and only makes simple modifications on the DETR decoder during training.

3 METHODOLOGY

3.1 OVERVIEW

We follow detection transformer (DETR) Carion et al. (2020) and adopt the transformer encoder and decoder structure. The image features are extracted with a backbone, then fed to the encoder to model the long-range dependencies. The decoder takes object queries as input and search for objects from the encoder feature with the cross-attention module. We illustrate the approach details in the following parts.

3.2 GROUP DETR

DETR replies on One-to-One assignment for end-to-end object detection but lacks of the capability of exploiting multiple positive queries. The decoder takes a group of $N$ queries as the input,

$$G^1 = \{q_1^1, \ldots, q_N^1\},$$ (1)

Each query in the decoder is responsible for predicting either a detection (class and bounding box) or a “no object” class. The query may come in different forms, including the high-dimensional feature vector used in DETR Carion et al. (2020), and the box coordinates used in DAB-DETR Liu et al. (2022). During training, the Hungarian algorithm (Kuhn, 1955) is employed to find an optimal One-to-One assignment $\sigma$ between predicted and ground-truth objects.
Figure 2: **Architecture of Group DETR.** Here we show one decoder layer for an example. We feed $K$ groups of queries to the decoder and conduct self-attention on each group of queries with the shared parameters. Then we make One-to-One assignment for each group. We omit the details of the cross-attention design in this figure.

$$\hat{\sigma} = \arg \min_{\sigma \in \xi_N} \sum_{i=1}^{N} C_{\text{match}}(y_i, \hat{y}_{\sigma(i)}),$$

(2)

$$C_{\text{match}} = \sum_{i=1}^{M} [\mu_{\text{cls}} \ell_{\text{FL}}(p_{\hat{\sigma}(i)}, \bar{c}_i) + \ell_{\text{box}}(b_{\hat{\sigma}(i)}, \bar{b}_i)].$$

(3)

where $\xi_N$ is the set of permutations of $N$ elements and $C_{\text{match}}(y_i, \hat{y}_{\sigma(i)})$ is the matching cost between ground truth $y_i$ and the prediction with index $\sigma(i)$. Each element of ground truth can be seen as $y_i = (\bar{c}_i, \bar{b}_i)$ where $\bar{c}_i$ is the target class label and $\bar{b}_i$ is the vector that defines the ground truth box. Similarly, the prediction is defined as $\hat{y}_{\sigma(i)} = (p_{\hat{\sigma}(i)}, b_{\hat{\sigma}(i)})$. $M$ is the number of ground-truth objects. $\ell_{\text{FL}}$ is the focal loss and $\mu_{\text{cls}} = 2$ is the trade-off coefficient. $\bar{c}_i$ is the class of the $i$-th ground-truth box and $\bar{c}_i = \text{null}$ if $i > M$. $\bar{b}_i$ is the $i$-th ground-truth box and $\ell_{\text{box}}$ is a combination of $\ell_1$ loss and GIoU loss [Rezatofighi et al. (2019)] and the loss weights are 5 and 2, respectively.

**Decoupled One-to-Many Assignment.** To enlarge the number of positive queries while avoiding duplicate predictions, we propose the decoupled One-to-Many assignment strategy. Given the number of positive queries $K$ that we want to match with each ground-truth object, we generate $K$ groups of queries (including the original group):
\[ G^1 = \{ q_1^1, \ldots, q_N^1 \}, \]
\[ \ldots \]
\[ G^K = \{ q_1^K, \ldots, q_N^K \}, \]

(4)  

The total \( K \) groups are fed to the decoder in parallel, but each group does not interact with other groups when performing decoder self-attention. Then One-to-One assignment is applied to the output of each group independently and we could get \( K \) matching results: \( \hat{\sigma}_1, \ldots, \hat{\sigma}_K \). The modifications during training are present in Figure 2 compared with the original DETR methods. During inference, only the first group is kept thus there is no extra cost compared with the original model.

3.3 DISCUSSION

3.3.1 EACH GROUP LEARS THE DISTRIBUTION OF OBJECT POSITIONS IN THE DATASET

We visualize the distribution of normalized query positions in Figure 3. We find that, the distributions of different groups are similar and queries from different groups are usually clustered together. We guess this is because they both learn the distribution of object positions in the dataset.

![Distribution of multiple group queries](image)

Figure 3: Distribution of multiple group queries. We show the normalized reference points of all groups based on the Conditional-DETR-C5. Different color represents different groups and the number of groups is 11. Best view in color.

![Two distance metrics (PD and MD) as a function of training steps](image)

Figure 4: Two distance metrics (PD and MD) as a function of training steps. The \( x \)-axis presents the training steps and the \( y \)-axis presents the relative length to the size of the original image. We use 3 groups in this experiment.

3.3.2 EACH GROUND-TRUTH BOX IS ASSIGNED TO QUERIES FROM DIFFERENT REGIONS

We define two distance metrics: perturbation distance PD and matching distance MD. Perturbation distance is the average distance between queries from the one group to the closest queries from the other group. We take the case of only 2 groups as an example:

\[
PD = \frac{1}{2N} \sum_{i=1}^{N} (\| \mathcal{P}(q_1^1), \mathcal{P}(N_{2\to1}(q_1^1)) \| + \| \mathcal{P}(q_2^1), \mathcal{P}(N_{1\to2}(q_2^1)) \|),
\]

(6)

where \( \mathcal{P}(\cdot) \) is the position of a query, \( N_{2\to1}(q_1^1) \) represents the closest query of \( q_1^1 \) in group \( G^2 \). \( \| a, b \| \) is the euclidean distance between two positions \( a \) and \( b \).

Matching distance is the average distance between query in one group and queries from other groups that match with the same ground-truth box:

\[ \| a, b \| \]
\[ \text{MD} = \frac{1}{M} \sum_{i=1}^{M} \| \mathcal{P}(q_{x_1(i)}), \mathcal{P}(q_{x_2(i)}) \|, \]

(7)

where \(M\) is the number of ground truth. \(x_1(i)\) is the query index the \(i\)-th ground truth matches with in group \(G_1\). We count these two distances during training in Figure 4. We find that MD is always significantly larger than PD, which illustrates that each ground-truth box is matched with multiple positive queries from different regions.

4 Experiments

4.1 Setting

Dataset. We perform the experiments on the COCO 2017 Lin et al. (2014) detection dataset, which contains about 118K training (\texttt{train}) images and 5K validation (\texttt{val}) images. Following the common practice, we report the standard mean average precision (AP) result on the COCO validation dataset under different IoU thresholds and object scales.

Training. We follow the DETR training protocol Carion et al. (2020). The backbone is the ImageNet-pretrained model from TORCHVISION with batchnorm layers fixed, and the transformer parameters are initialized using the Xavier initialization scheme Glorot & Bengio (2010). We train the model on the COCO training set for 12/50 epochs, with the AdamW Loshchilov & Hutter (2017) optimizer. The learning rate is dropped by a factor of 10 after 11/40 epochs. The weight decay is set to be \(10^{-4}\). The learning rates for the backbone and the transformer are initialized as \(10^{-5}\) and \(10^{-4}\), respectively. The number of decoder queries is set as 300 by default.

We use the augmentation scheme same as DETR Carion et al. (2020): resize the input image such that the short side is at least 480 and at most 800 pixels and the long side is at most 1333 pixels; randomly crop the image such that a training image is cropped with a probability 0.5 to a random rectangular patch.

4.2 Improvements on DETR-based methods

We apply our decoupled One-to-Many assignment to different DETR-based methods to verify the effectiveness, e.g., Conditional DETR Meng et al. (2021), DAB-DETR Liu et al. (2022), DN-DETR Li et al. (2022), DINO Zhang et al. (2022) and Mask2Former Cheng et al. (2021).

| Model          | #Groups | Schedule | mAP  | AP_s | AP_m | AP_l |
|---------------|---------|----------|------|------|------|------|
| Conditional DETR-C5 | 1       | 12e      | 32.6 | 14.7 | 35.0 | 48.3 |
| Conditional DETR-C5 | 2       | 12e      | 34.4 | 15.1 | 37.1 | 51.8 |
| Conditional DETR-C5 | 3       | 12e      | 35.3 | 15.7 | 38.5 | 53.3 |
| Conditional DETR-C5 | 4       | 12e      | 35.9 | 15.9 | 38.9 | 53.8 |
| Conditional DETR-C5 | 5       | 12e      | 36.5 | 15.8 | 39.7 | 54.6 |
| Conditional DETR-C5 | 6       | 12e      | 36.4 | 16.6 | 39.7 | 54.5 |
| Conditional DETR-C5 | 7       | 12e      | 36.8 | 16.8 | 40.2 | 54.8 |
| Conditional DETR-C5 | 9       | 12e      | 37.2 | 16.5 | 40.5 | 54.8 |
| Conditional DETR-C5 | 11      | 12e      | 37.6 (+5.0) | 18.2 | 40.7 | 55.9 |

Table 1: Experimental results based on Conditional DETR.

Conditional DETR. Conditional DETR uses a high-dimensional vector as the decoder query. We enlarge the number of groups from 1 to 11 in Table 1. Please note that only the first group is kept during inference. We observe consistent improvements over baseline and the model with 11 groups achieves 37.6 AP, which is 5.0 higher than the baseline.

DAB-DETR, DN-DETR and DINO. DAB-DETR uses a 4-D vector that represents an anchor box as the decoder query. Results are listed in Table 2. For the C5 model, The model trained with 11
Model #Groups Schedule mAP APs APm APl
DN-DETR-C5 1 12e 38.6 17.9 41.6 57.7
DN-DETR-C5 7 12e 40.3(+1.7) 20.0 43.8 59.5
DAB-DETR-C5 1 12e 35.2 16.7 38.6 51.6
DAB-DETR-C5 11 12e 39.1(+3.9) 19.7 42.5 56.8
DAB-DETR-DC5 1 12e 41.9(+4.4) 23.3 45.6 58.4
DAB-Deformable-DETR 1 12e 44.2 27.5 47.1 58.6
DAB-Deformable-DETR 11 12e 45.7(+1.5) 28.1 49.0 60.6
DINO-Deformable-DETR 1 12e 48.8 31.0 52.0 62.4
DINO-Deformable-DETR 3 12e 49.8(+1.0) 32.4 53.0 64.2
DAB-DETR-C5 1 50e 42.2 21.5 45.7 60.3
DAB-DETR-C5 11 50e 44.5(+2.3) 24.2 48.5 63.2
DAB-DETR-DC5 1 50e 44.5 25.3 48.2 62.3
DAB-DETR-DC5 11 50e 46.7(+2.2) 27.6 50.9 64.0
DAB-Deformable-DETR 1 50e 48.1 31.4 51.4 63.4
DAB-Deformable-DETR 11 50e 49.7(+1.6) 31.4 52.5 65.6

Table 2: Experimental results based on DAB-DETR, DN-DETR and DINO.

Model #Groups Schedule mAPm APs APm APl
Mask2Former 1 12e 38.5 17.6 41.4 60.4
Mask2Former 11 12e 39.5(+1.0) 18.8 42.4 60.8

Table 3: Experimental results based on Mask2Former. The metric mAPm in the table represents the mask AP for instance segmentation.

5 C O N C L U S I O N

In this paper, we present Group DETR to support multiple positive queries. Group DETR uses Decoupled One-to-Many label assignment to achieve end-to-end object detection. In detail, we decouple the positive queries into multiple independent groups and conduct One-to-One assignment in each group. During testing, only one group is kept and there is no extra computational cost brought compared to the original model. We hope our Decoupled One-to-Many assignment will motivate researchers to explore more in this direction.

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