DAC-DETR: Divide the Attention Layers and Conquer

A Supplementary Material

A.1 Gathering effect on more decoder layers

Section 3.3 (Mechanism Analysis) in the main text shows that DAC-DETR improves the gathering effect of the cross-attention layer, *i.e.* more and better queries (Fig. 3 in the main text). We supplement results on more decoder layers (layer-2, layer-3 and layer-4) in Fig. A1.

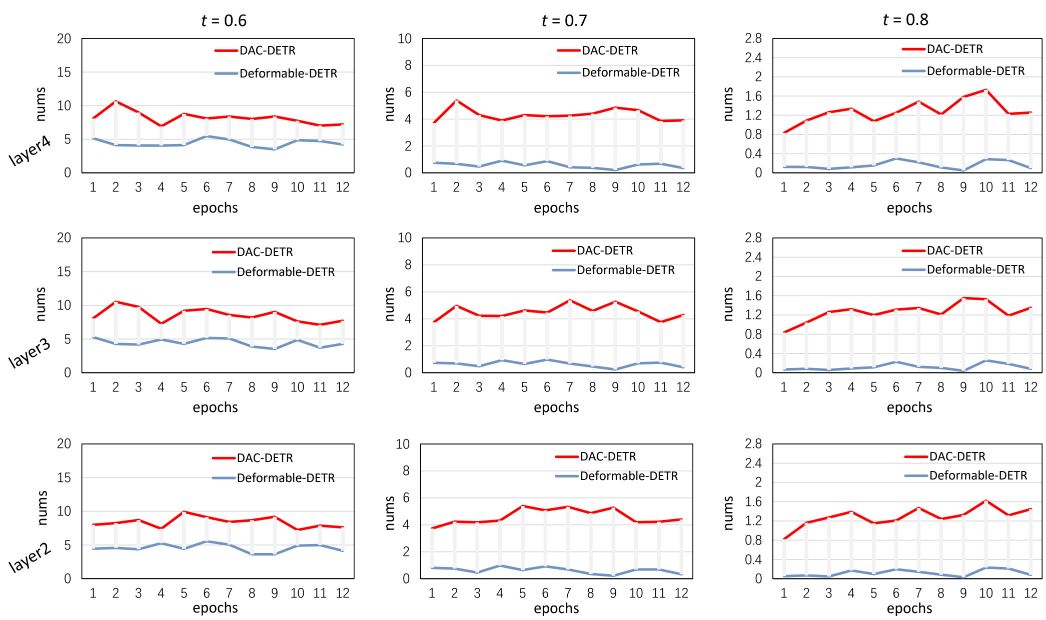


Figure A1: The averaged number of queries that each ground-truth object gathers on the validation set of MS-COCO.

The observation in Fig. A1 is consistent with Fig. 3 in the main text: DAC-DETR gathers more queries for each single object and improves the quality of the best queries. The two corresponding remarks, *i.e.*, DAC-DETR improves the quantity and quality of the gathered queries, hold across multiple decoder layers.

A.2 Comparison on Convergence Speed

We investigate the convergence speed of DAC-DETR on three baselines (Deformable-DETR [8] , Deformable-DETR++ [3], and DINO [7]) in Fig. A2. The experiments are conducted on the COCO 2017 [4] detection validation dataset. We adopt ResNet50 [2] backbone and run 12 epochs. It is observed that DAC-DETR consistently improves the convergence speed over all three baselines. For example, DAC-DETR outperforms the Deformable-DETR baseline by +8.3 AP and +3.4 AP at epoch-1 and epoch-12, respectively.

Submitted to 37th Conference on Neural Information Processing Systems (NeurIPS 2023). Do not distribute.

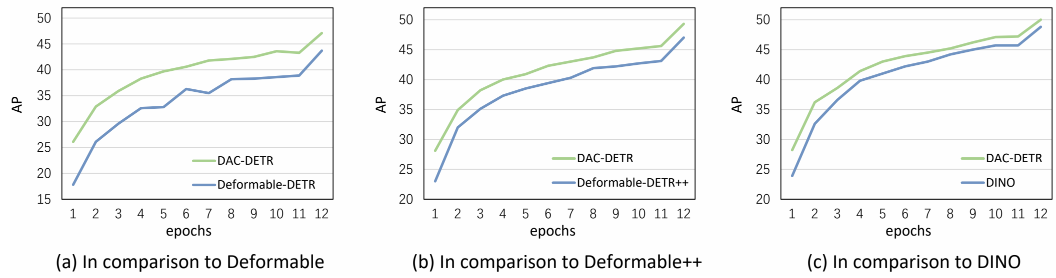


Figure A2: Comparison of convergence speed between DAC-DETR and three baselines.

A.3 Comparison of training time and inference FPS

We compare the average training time per epoch and the inference FPS between DAC-DETR, H-DETR [3], and baseline method (Deformable-DETR [8]). For a fair comparison, all the methods utilize 8 A100 GPUS for training and a single A100 GPU for inference.

Method	Backbone	Training time (average)	Inference FPS	AP
Basel (Deformable) [8]	R50	58 min	17.8	43.7
H-DETR [3]	R50	70 min	17.8	45.9
DAC-DETR (ours)	R50	64 min	17.8	47.1

Table A1: Comparison of average training time on each epoch and inference FPS.

From Table A1, we draw two observations: 1) Compared to the baseline, DAC-DETR increases the training time per epoch by a small margin (*i.e.*, +6 minutes) while maintaining the same inference efficiency. The small increase on training time is because DAC-DETR additionally introduces an auxiliary decoder (*i.e.*, C-Decoder) that processes all the queries in parallel. 2) Compared with H-DETR (a recent method that employs auxiliary decoder branch), our DAC-DETR is faster to train (-6 minutes per epoch). There are two reasons: first, DAC-DETR uses fewer queries than H-DETR. Second, the auxiliary C-Decoder in DAC-DETR has fewer attention layers (*i.e.*, no self-attention layers).

A.4 More hyper-parameter analysis

In our one-to-many label assignment (Eqn.4 in the main text), we compute the matching score m between each query and the object by adding their IoU score and the predicted label score on the ground-truth class. To introduce more flexibility, we combine these two scores through a weighted sum, which is formulated as:

$$m = (1-\lambda)\cdot p_{(q)}(\hat{c}) + \lambda \cdot \texttt{IoU} < b_{(q)}, \hat{b} >, \tag{1}$$

where λ is a newly-added hyper-parameter for weighting, and all the other variables are the same as in the main text (*i.e.*, $\hat{c}$ and $\hat{b}$ are the class and bounding box of query q, $p_{(q)}(\hat{c})$ denotes the predicted label score on class $\hat{c}$. $b_{(q)}$ denotes the predicted box, $<,>$ denotes the IoU operation between predicted box and ground truth $\hat{b}$). We investigate the influence of this hyper-parameter λ in Table A2.

λ	0.5	0.6	0.7	0.8	0.9	1.0
AP	46.8	47.0	47.1	47.0	46.8	46.6

Table A2: Analysis on the weight λ in the one-to-many label assignment. We adopt Deformable-DETR as the baseline.

We observe that DAC-DETR is robust to this hyper-parameter within a large range, and in practice use $\lambda = 0.7$ for all the experiments.

A.5 More Experiments

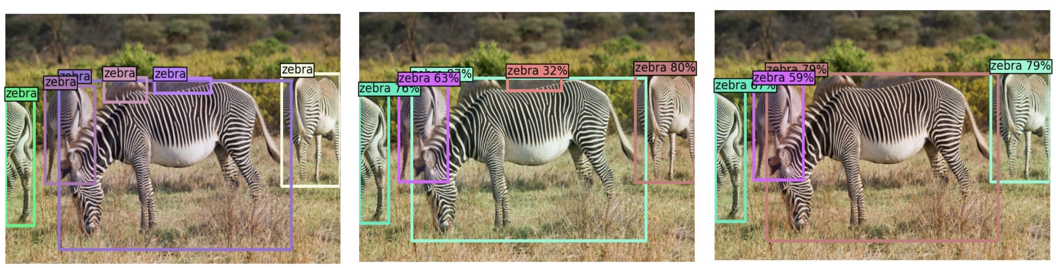
We evaluate the performance of Align-DETR [1] with the Swin-L [6] backbone on COCO 2017 detection validation dataset, using the official publicly codes. (Align-DETR does not report the results with Swin-L backbone). The results in Table A3 further confirms the superiority of DAC-DETR. After combining an IoU-related loss (Align loss), DAC-DETR surpasses Align-DETR by +0.7 AP (12 epochs).

Method	Backbone	epochs	AP	AP_{50}	AP_{75}	AP_S	AP_M	AP_L
Basel (DINO) [7]	Swin-L	12	56.8	75.6	62.0	40.0	60.5	73.2
Align-DETR † [1]	Swin-L	12	57.4	75.9	62.2	40.6	61.6	73.7
Stable-DINO-4scale [5]	Swin-L	12	57.7	75.7	63.4	39.8	62.0	74.7
DAC-DETR + Align (ours)	Swin-L	12	58.1	76.5	63.3	40.9	62.4	75.0

Table A3: Evaluation on COCO val2017 with Swin-Transformer Large backbone. †: We evaluate Align-DETR using the official publicly codes.

A.6 Visualization of Object Detection

We visualize some detection results with predicted bounding boxes and label scores in Fig. A3 and Fig. A4. As shown in Fig. A3, DAC-DETR detects the object "zebra" with limited semantic information, whereas Deformable-DETR fails to do so. Compared to Deformable-DETR++, DAC-DETR provides more accurate label and box predictions for the object "cat", as shown in Fig. A4.



(a) ground truth (b) DAC-DETR (c) Deformable-DETR

Figure A3: Visualization of the detection results of DAC-DETR and Deformable-DETR.

(a) ground truth (b) DAC-DETR (c) Deformable-DETR++

Figure A4: Visualization of the detection results of DAC-DETR and Deformable-DETR++.

References

[1] Zhi Cai, Songtao Liu, Guodong Wang, Zheng Ge, Xiangyu Zhang, and Di Huang. Align-detr: Improving detr with simple iou-aware bce loss, 2023.

[2] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 770–778, 2016.

[3] Ding Jia, Yuhui Yuan, Haodi He, Xiaopei Wu, Haojun Yu, Weihong Lin, Lei Sun, Chao Zhang, and Han Hu. Detrs with hybrid matching. *arXiv preprint arXiv:2207.13080*, 2022.

[4] Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C Lawrence Zitnick. Microsoft coco: Common objects in context. In *Computer Vision–ECCV 2014: 13th European Conference, Zurich, Switzerland, September 6-12, 2014, Proceedings, Part V 13*, pages 740–755. Springer, 2014.

[5] Shilong Liu, Tianhe Ren, Jiayu Chen, Zhaoyang Zeng, Hao Zhang, Feng Li, Hongyang Li, Jun Huang, Hang Su, Jun Zhu, and Lei Zhang. Detection transformer with stable matching, 2023.

[6] Ze Liu, Yutong Lin, Yue Cao, Han Hu, Yixuan Wei, Zheng Zhang, Stephen Lin, and Baining Guo. Swin transformer: Hierarchical vision transformer using shifted windows. In *Proceedings of the IEEE/CVF international conference on computer vision*, pages 10012–10022, 2021.

[7] Hao Zhang, Feng Li, Shilong Liu, Lei Zhang, Hang Su, Jun Zhu, Lionel M. Ni, and Heung-Yeung Shum. Dino: Detr with improved denoising anchor boxes for end-to-end object detection, 2022.

[8] Xizhou Zhu, Weijie Su, Lewei Lu, Bin Li, Xiaogang Wang, and Jifeng Dai. Deformable detr: Deformable transformers for end-to-end object detection. *arXiv preprint arXiv:2010.04159*, 2020.