UP-DETR: Unsupervised Pre-training for Object Detection with Transformers

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Abstract
Object detection with transformers (DETR) reaches competitive performance with Faster R-CNN via a transformer encoder-decoder architecture. Inspired by the great success of pre-training transformers in natural language processing, we propose a pretext task named random query patch detection to unsupervisedly pre-train DETR (UP-DETR) for object detection. Specifically, we randomly crop patches from the given image and then feed them as queries to the decoder. The model is pre-trained to detect these query patches from the original image. During the pre-training, we address two critical issues: multi-task learning and multi-query localization. (1) To trade-off multi-task learning of classification and localization in the pretext task, we freeze the CNN backbone and propose a patch feature reconstruction branch which is jointly optimized with patch detection. (2) To perform multi-query localization, we introduce UP-DETR from single-query patch and extend it to multi-query patches with object query shuffle and attention mask. In our experiments, UP-DETR significantly boosts the performance of DETR with faster convergence and higher precision on PASCAL VOC and COCO datasets. The code will be available soon.

1. Introduction
Object detection with transformers (DETR) [4] is a recent framework that views object detection as a direct prediction problem via a transformer encoder-decoder [33]. Without hand-designed sample selection [39] and non-maximum suppression, DETR reaches a competitive performance with Faster R-CNN [28]. However, DETR comes with training and optimization challenges, which needs large-scale training data and an extreme long training schedule. As shown in Fig. 1 and Section 4.1, we find that DETR performs poorly in PASCAL VOC [12], which has insufficient training data and fewer instances than COCO [22].

With well-designed pretext tasks, unsupervised pre-training models achieve remarkable progress in both natural language processing (e.g. GPT [26, 27] and BERT [10]) and computer vision (e.g. MoCo [15, 8] and SwAV [6]). In DETR, the CNN backbone (ResNet-50 [18] with ∼23.2M parameters) has been pre-trained to extract a good visual representation, but the transformer module with ∼18.0M parameters has not been pre-trained. More importantly, although unsupervised visual representation learning (e.g. contrastive learning) attracts much attention in recent studies [15, 7, 13, 3, 5, 1], existing pretext tasks can not directly apply to pre-train the transformers of DETR. The main reason is that DETR mainly focuses on spatial localization learning instead of image instance-based [15, 7, 13] or cluster-based [3, 5, 1] contrastive learning.

Inspired by the great success of unsupervised pre-
training in natural language processing [10], we aim to unsupervisedly pre-train the transformers of DETR on a large-scale dataset (e.g. ImageNet), and treat object detection as the downstream task. The motivation is intuitive, but existing pretext tasks seem to be impractical to pre-train the transformers of DETR. To overcome this problem, we propose a novel unsupervised pretext task named **random query patch detection** to pre-train the detector without any human annotations — we randomly crop multiple query patches from the given image, and pre-train the transformers for detection to predict bounding boxes of these query patches in the given image. During the pre-training procedure, we address two critical issues as follows:

(1) Multi-task learning: Object detection is the coupling of object classification and localization. To avoid query patch detection destroying the classification features, we introduce **frozen pre-training backbone** and **patch feature reconstruction** to preserve the feature discrimination of transformers.

(2) Multi-query localization: Different object queries focus on different position areas and box sizes. To illustrate this property, we propose a simple single-query pre-training and extend it to a multi-query version. For multi-query patches, we design **object query shuffle** and **attention mask** to solve the assignment problems between query patches and object queries.

In this paper, the proposed detector is named as **Unsupervised Pre-training DETR (UP-DETR)**. We evaluate the performance of UP-DETR against a highly optimized Faster R-CNN and DETR baseline on two popular object detection datasets: PASCAL VOC [12] and COCO [22]. For VOC dataset, UP-DETR significantly surpasses the precision of the original DETR by a large margin with faster convergence. For the challenging COCO dataset with sufficient training data, UP-DETR obtains 42.8 AP with ResNet-50, which still outperforms DETR in both convergence speed and precision.

### 2. Related Work

#### 2.1. Object Detection

Most object detection methods mainly differ in positive and negative sample assignment. Two-stage detectors [28, 2] and a part of one-stage detectors [21, 23] construct positive and negative samples by hand-crafted multi-scale anchors with the IoU threshold and model confidence. Anchor-free one-stage detectors [32, 40] assign positive and negative samples to feature maps by a grid of object centers. Zhang et al. [39] demonstrate that the performance gap between them is due to the selection of positive and negative training samples. DETR [4] is a recent object detection framework that is conceptually simpler without hand-crafted process by direct set prediction [31], which assigns the positive and negative samples automatically.

Apart from the positive and negative sample selection problem, the trade-off between classification and localization is also intractable for object detection. Zhang et al. [38] demonstrate that there is a domain misalignment between classification and localization. Wu et al. [34] and Song et al. [29] design two head structures for classification and localization. They point out that these two tasks may have opposite preferences. For our pre-training model, it maintains shared feature for classification and localization. Therefore, it is essential to take a well trade-off between these two tasks.

#### 2.2. Unsupervised Pre-training

Unsupervised pre-training models always follow two steps: pre-training on a large-scale dataset with the pretext task and fine-tuning the parameters on downstream tasks. For unsupervised pre-training, the pretext task is always invented, and we are interested in the learned intermediate representation rather than the final performance of the pretext task.

To perform unsupervised pre-training, there are various well-designed pretext tasks. For natural language processing, utilizing time sequence relationship between discrete tokens, masked language model [10], permutation language model [36] and auto regressive model [26, 27] are proposed to pre-train transformers [33] for language representation. For computer vision, unsupervised pre-training models also achieve remarkable progress recently for visual representation learning, which outperform the supervised learning counterpart in downstream tasks. Instance-based discrimination tasks [37, 35] and clustering-based tasks [5] are two typical pretext tasks in recent studies. Instance-based discrimination tasks vary mainly on maintaining different sizes of negative samples [15, 7, 13] with non-parametric contrastive learning [14]. Moreover, instance discrimination can also be performed as parametric instance classification [3]. Clustering-based tasks vary on offline [5, 1] or online clustering procedures [6]. UP-DETR is a novel pretext task, which aims to pre-train transformers based on the DETR architecture for object detection.

### 3. UP-DETR

The proposed UP-DETR contains pre-training and fine-tuning procedures: (a) the transformers are unsupervisedly pre-trained on a large-scale dataset without any human annotations; (b) the entire model is fine-tuned with labeled data which is same as the original DETR [4] on the downstream tasks. In this section, we mainly describe how to pre-train the transformer encoder and decoder with random query patch detection.
As shown in Fig. 2, the main idea of random query patch detection is simple but effective. Firstly, a frozen CNN backbone is used to extract a visual representation with the feature map $f \in \mathbb{R}^{C \times H \times W}$ of an input image, where $C$ is the channel dimension and $H \times W$ is the feature map size. Then, the feature map is added with positional encodings and passed to the multi-layer transformer encoder in DETR. For the random cropped query patch, the CNN backbone with global average pooling (GAP) extracts the patch feature $p \in \mathbb{R}^C$, which is flatten and supplemented with object queries $q \in \mathbb{R}^C$ before passing it into a transformer decoder. Noting that the query patch refers to the cropped patch from the original image but object query refers to position embeddings, which are fed to the decoder. The CNN parameters are shared in the whole model.

During the pre-training procedure, the decoder predicts the bounding boxes corresponding to the position of random query patches in the input image. Assuming that there are $M$ query patches by random cropping, the model infers a prediction fixed-set $\hat{y} = \{\hat{y}_i\}_{i=1}^{N}$ corresponding to $N$ object queries ($N > M$). For better understanding, we will describe the training details of single-query patch ($M = 1$) in Section 3.1, and extend it to multi-query patches ($M > 1$) with object query shuffle and attention mask in Section 3.2.

### 3.1. Single-query Patch

DETR learns different spatial specialization for each object query [4], which indicates that different object queries focus on different position areas and box sizes. As we randomly crop the patch from the image, there is no any priors about the position areas and box sizes of the query patch. To preserve the different spatial specialization, we explicitly specify single-query patch ($M = 1$) to all object queries ($N = 3$) as shown in Fig. 2a.

During the pre-training procedure, the patch feature $p$ is added to each different object query $q_i$, and the decoder generates $N$ pairs of predictions $\hat{y}_i = \{\hat{y}_i\}_{i=1}^{N}$ to detect the bounding box of query patch in the input image. Following DETR [4], we compute the same match cost between the prediction $\hat{y}_i$ and the ground-truth $y_i$ using Hungarian algorithm [31], where $\hat{\sigma}(i)$ is the index of $y_i$ computed by the optimal bipartite matching.

For the loss calculation, the predicted result $\hat{y}_i = (\hat{c}_i, \hat{b}_i, \hat{\sigma}(i))$ consists of three elements: $\hat{c}_i$ is the binary classification of matching the query patch ($c_i = 1$) or not ($c_i = 0$) for each object query; $\hat{b}_i$ is the vector that defines the box center coordinates, its width and height $\{x, y, w, h\}$. They are re-scaled relative to the image size; $\hat{\sigma}(i)$ is the reconstructed feature with $C = 2048$ for the ResNet-50 backbone typically. With the above definitions, the Hungarian loss for all matched pairs is defined as:

$$
\mathcal{L}(y, \hat{y}) = \sum_{i=1}^{N} \left[ \lambda_{\{c_i=1\}} \mathcal{L}_{cls}(c_i, \hat{c}_i, \hat{\sigma}(i)) \right] + \mathbb{I}_{\{c_i=1\}} \mathcal{L}_{box}(b_i, \hat{b}_i, \hat{\sigma}(i)) + \mathbb{I}_{\{c_i=1\}} \mathcal{L}_{rec}(p_i, \hat{p}_{\hat{\sigma}(i)})]
$$

Here, $\mathcal{L}_{cls}$ is the cross entropy loss over two classes (match the query patch vs. not match), and the class balance weight $\lambda_{\{c_i=1\}} = 1$ and $\lambda_{\{c_i=0\}} = M/N$. $\mathcal{L}_{box}$ is a linear combination of $\ell_1$ loss and the generalized IoU loss with the same weight hyper-parameters as DETR [4]. $\mathcal{L}_{rec}$ is the reconstruction loss proposed in this paper to balance classification and localization during the unsupervised pre-training, which will be discussed in detail below.

### 3.1.1 Patch Feature Reconstruction

Object detection is the coupling of object classification and localization, where these two tasks always have different
feature preferences [38, 34, 29]. Different from DETR, we propose a feature reconstruction term $\mathcal{L}_{\text{rec}}$ to preserve classification feature during localization pre-training. The motivation of this term is to preserve the feature discrimination extract by CNN after passing feature to transformers. $\mathcal{L}_{\text{rec}}$ is the mean squared error between the $\ell_2$-normalized patch feature extracted by the CNN backbone, which is defined as follows:

$$\mathcal{L}_{\text{rec}}(p_i, \hat{p}_{\sigma(i)}) = \frac{1}{\|p_i\|^2_2} \left\| \frac{p_i}{\|p_i\|^2_2} - \frac{\hat{p}_{\sigma(i)}}{\|\hat{p}_{\sigma(i)}\|^2_2} \right\|^2_2.$$  

(2) Diversity of object queries. There are no fixed group-wise relations between the object queries from the same group. Therefore, a query patch should correspond to various object queries. In other words, the query patch can be added to arbitrary $N/M$ object queries ideally.

3.2.1 Attention Mask

To satisfy the independence of query patches, we utilize an attention mask matrix to control the interactions between different object queries. The mask matrix $X \in \mathbb{R}^{N \times N}$ is added to the softmax layer of self-attention in the decoder $\text{softmax}(QK^\top / \sqrt{d_k} + X) V$. Similar to the token mask in UniLM [11], the attention mask is defined as:

$$X_{i,j} = \begin{cases} 0, & i, j \text{ in the same group} \\ -\infty, & \text{otherwise} \end{cases}.$$  

(3) where $X_{i,j}$ determines whether the object query $q_i$ attends to the interaction with the object query $q_j$. For intuitive understanding, the attention mask in Fig. 2b displays 1 and 0 corresponding to 0 and $-\infty$ in (3), respectively.

3.2.2 Object Query Shuffle

To satisfy the diversity of object queries, we randomly shuffle the permutation of all the object query embeddings during pre-training. Due to object query shuffle, the attention mask and the query patch assignment can be fixed in practice.

Fig. 2b illustrates the pre-training of multi-query patches with attention mask and object query shuffle. To improve the generalization, we randomly mask 10% query patches to zero during pre-training similarly to dropout [30]. In our experiments, two typical values are set to $N = 100$ and $M = 10$. Apart from such modifications, other training settings are the same as those described in Section 3.1.

4. Experiments

We pre-train the model using ImageNet [9] and fine-tune the parameters on VOC [12] and COCO [22]. In all experiments, we adopt the UP-DETR model (41.3M parameters) with ResNet-50 backbone, 6 transformer encoder, 6 decoder layers of width 256 with 8 attention heads. Referring to the open source of DETR, we use the same hyperparameters in the proposed UP-DETR and our DETR re-implementation. We annotate R50 and R101 short for ResNet-50 and ResNet-101.

Pre-training setup. UP-DETR is unsupervisedly pre-trained on the 1.28M ImageNet training set without any labels. The CNN backbone (ResNet-50) is also unsupervisedly pre-trained with SwAV [6], and its parameters are

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3https://github.com/facebookresearch/detr
frozen during UP-DETR pre-training. As the input image from ImageNet is relatively small, we resize it such that the shortest side is within $[320, 480]$ pixels while the longest side is at most 600 pixels. For the given image, we crop the query patches with random coordinate, height and width, which are resized to $128 \times 128$ pixels and transformed with the SimCLR-style [7] without horizontal flipping, including random color distortion and Gaussian blurring. AdamW [24] is used to optimize the UP-DETR, with the initial learning rate of $1 \times 10^{-4}$ and the weight decay of $1 \times 10^{-4}$. We use a mini-batch size of 256 on 8 V100 GPUs to train the model for 60 epochs with the learning rate multiplied by 0.1 at 40 epochs.

**Fine-tuning setup.** The model is initialized with pre-training UP-DETR parameters and fine-tuned for all the parameters (including CNN) on VOC and COCO. We fine-tune the model with the initial learning rate $1 \times 10^{-4}$ for transformers and $5 \times 10^{-5}$ for CNN backbone, and the other settings are same as DETR [4] on 8 V100 GPUs with 4 images per GPU. The model is fine-tuned with short/long schedule for 150/300 epochs and the learning rate is multiplied by 0.1 at 100/200 epochs, respectively.

### 4.1. PASCAL VOC Object Detection

**Setup.** The model is fine-tuned on VOC trainval07+12 (≈16.5k images) and evaluated on test2007. We report COCO-style metrics, including AP, AP$_{50}$ (default VOC metric) and AP$_{75}$. For a full comparison, we also report the result of Faster R-CNN with the R50-C4 backbone [6], which performs much better than R50 [19]. DETR with R50-C4 significantly increases the computational cost than R50, so we fine-tune UP-DETR with R50 backbone. Here, the CNN backbone is pre-trained with SwA V [6]. To emphasize the effectiveness of pre-training models, we report the results of 150 and 300 epochs for both DETR and UP-DETR.

| Model/Epoch | AP  | AP$_{50}$ | AP$_{75}$ |
|-------------|-----|----------|----------|
| Faster R-CNN | 56.1 | 82.6     | 62.7     |
| DETR/150    | 49.9 | 74.5     | 53.1     |
| UP-DETR/150 | 56.1 (+6.2) | 79.7 (+5.2) | 60.6 (+7.5) |
| DETR/300    | 54.1 | 78.0     | 58.3     |
| UP-DETR/300 | 57.2 (+3.1) | 80.1 (+2.1) | 62.0 (+3.7) |

Table 1: Object detection results trained on PASCAL VOC trainval07+12 and evaluated on test2007. DETR and UP-DETR use R50 backbone and Faster R-CNN uses R50-C4 backbone. The values in the brackets are the gaps compared to DETR with the same training schedule.

**Results.** Table 1 shows the compared results of PASCAL VOC. We find that the DETR performs poorly in PASCAL VOC, which is much worse than Faster R-CNN by a large gap in all metrics. Due to the relatively small-scale data in VOC, the pre-training transformers of UP-DETR significantly boosts the performance of DETR for both short and long schedules: up to +6.2 (+3.1) AP, +5.2 (+2.1) AP$_{50}$ and +7.5 (+3.7) AP$_{75}$ for 150 (300) epochs, respectively. Moreover, UP-DETR (R50) achieves a comparable result to Faster R-CNN (R50-C4) with better AP. We find that both UP-DETR and DETR perform a little worse than Faster R-CNN in AP$_{50}$ and AP$_{75}$. It may come from different ratios of feature maps (C4 for Faster R-CNN) and no NMS post-processing (NMS lowers AP but slightly improves AP$_{50}$).

Fig. 3a shows the AP (COCO style) learning curves on VOC. UP-DETR significantly speeds up the model convergence. After the learning rate reduced, UP-DETR significantly boosts the performance of DETR with a large AP improvement. Noting that UP-DETR obtains 56.1 AP after 150 epochs, however, its counterpart DETR (scratch transformers) only obtains 54.1 AP even after 300 epochs and does not catch up even training longer. It suggests that pre-training transformers is indispensable on insufficient training data (i.e. $\sim 16.5$K images on VOC).

### 4.2. COCO Object Detection

**Setup.** The model is fine-tuned on COCO train2017 (≈118k images) and evaluated on val2017. There are lots of small objects in COCO dataset, where DETR performs poorly [4]. Therefore, we report AP, AP$_{50}$, AP$_{75}$, AP$_S$, AP$_M$ and AP$_L$ for a comprehensive comparison. Moreover, we also report the results of highly optimized Faster R-CNN-FPN with short ($3 \times$) and long ($9 \times$) training schedules, which are known to improve the performance results [16]. To avoid supervised CNN bringing supplementary information, we use SwA V pre-training CNN as the backbone of UP-DETR without any human annotations.

**Results.** Table 2 shows the results on COCO with other methods. With 150 epoch schedule, UP-DETR outperforms DETR by 0.8 AP and achieves a comparable performance as compared with Faster R-CNN-FPN ($3 \times$ schedule). With 300 epoch schedule, UP-DETR obtains 42.8 AP on COCO, which is 0.7 AP better than DETR (SwA V CNN) and 0.8 AP better than Faster R-CNN-FPN ($9 \times$ schedule). Overall, UP-DETR comprehensively outperforms DETR in detection of small, medium and large objects with both short and long training schedules. Regrettably, UP-DETR is still slightly lagging behind Faster R-CNN in AP$_S$, because of the lacking of FPN-like architecture [20].

Fig. 3b shows the AP learning curves on COCO. UP-DETR outperforms DETR for both 150 and 300 epoch schedules with faster convergence. The performance improvement is more noticeable before reducing the learning rate. After reducing the learning rate, UP-DETR still holds the lead of DETR by $\sim 0.7$ AP improvement. It suggests that pre-training transformers is still indispensable even on
Model | Backbone | Epochs | AP | AP50 | AP75 | APs | APM | APL
--- | --- | --- | --- | --- | --- | --- | --- | ---
Faster R-CNN † [20] | R101-FPN | - | 36.2 | 59.1 | 39.0 | 18.2 | 39.0 | 48.2
Mask R-CNN † [17] | R101-FPN | - | 38.2 | 60.3 | 41.7 | 20.1 | 41.1 | 50.2
Grid R-CNN † [25] | R101-FPN | - | 41.5 | 60.9 | 44.5 | 23.3 | 44.9 | 53.1
Double-head R-CNN [34] | R101-FPN | - | 41.9 | 62.4 | 45.9 | 23.9 | 45.2 | 55.8
RetinaNet † [21] | R101-FPN | - | 39.1 | 60.7 | 45.0 | 24.4 | 44.8 | 51.6
FCOS † [32] | R101-FPN | - | 41.5 | 60.7 | 45.0 | 24.4 | 44.8 | 51.6
DETR [4] | R50 | 500 | 42.0 | 62.4 | 44.2 | 20.5 | 45.8 | 61.1

Table 2: Object detection results trained on COCO train2017 and evaluated on val2017. Faster R-CNN, DETR and UP-DETR are performed under comparable settings. † for values evaluated on COCO test-dev, which are always slightly higher than val2017. The values in the brackets are the gaps compared to DETR (SwAV CNN) with the same training schedule.

![AP learning curves of VOC](image1)

![AP learning curves of COCO](image2)

Figure 3: AP (COCO style) learning curves with DETR and UP-DETR on VOC and COCO. Models are trained with the SwAV pre-training ResNet-50 for 150 and 300 epochs, and the learning rate is reduced at 100 and 200 epochs, respectively.

4.3. Ablations

For ablation experiments, we pre-train UP-DETR with four different settings for 15 epochs with the learning rate multiplied by 0.1 at the 10-th epoch. We fine-tune the models on PASCAL VOC following the setup in Section 4.1 with 150 epochs. Therefore, the results in ablations are relatively lower than those shown in Section 4.1.

4.3.1 Single-query patch vs. Multi-query patches

We pre-train two models with single-query patch ($M = 1$) and multi-query patches ($M = 10$). The other hyper-parameters are set as mentioned above.

Table 3 shows the results of single-query patch and multi-query patches. Compared with DETR, UP-DETR surpasses it in all AP metrics by a large margin no matter with single-query patch or multi-query patches. When
pre-training UP-DETR with the different number of query patches, UP-DETR ($M = 10$) performs better than UP-DETR ($M = 1$) on the fine-tuning task, although there are about 2.3 instances per image on VOC. Therefore, we adopt the same UP-DETR with $M = 10$ for both VOC and COCO instead of varying $M$ for different downstream tasks.

| Model       | AP  | AP$_{50}$ | AP$_{75}$ |
|-------------|-----|-----------|-----------|
| DETR        | 49.9| 74.5      | 53.1      |
| UP-DETR ($M=1$) | 53.1 (+3.2) | 77.2 (+2.7) | 57.4 |
| UP-DETR ($M=10$) | **54.9 (+5.0)** | **78.7 (+4.2)** | **59.1** |

Table 3: The ablation results of pre-training models with single-query patch and multi-query patches on PASCAL VOC. The values in the brackets are the gaps compared to the DETR with the same training schedule.

| Case  | Frozen CNN | Feature Reconstruction | AP$_{50}$ |
|-------|------------|------------------------|-----------|
| DETR  | scratch transformers | ✓                     | 74.5      |
| (a)   | ✓          | ✓                      | 74.0      |
| (b)   | ✓          | ✓                      | **78.7** |
| (c)   | ✓          | ✓                      | 62.0      |
| (d)   | ✓          | ✓                      | **78.7** |

Table 4: Ablation study on frozen CNN and feature reconstruction for pre-training models with AP$_{50}$. The experiments are fine-tuned on PASCAL VOC with 150 epochs.

4.3.2 Frozen CNN and Feature Reconstruction

To illustrate the importance of patch feature reconstruction and frozen CNN backbone of UP-DETR, we pre-train four different UP-DETR models with different combinations of whether freezing CNN and whether adding feature reconstruction. Noting that all the models (including DETR) use the pre-trained CNN on ImageNet.

Table 4 shows AP and AP$_{50}$ of four different pre-training models and DETR on VOC with 150 epochs. As shown in Table 4, not all pre-trained models are better than DETR, and pre-training models (b) and (d) perform better than the others. More importantly, without frozen CNN, pre-training models (a) and (c) even perform worse than DETR. It confirms that freezing pre-trained CNN is essential to pre-train transformers. In addition, it further confirms the pretext (random query patch detection) may weaken the feature discrimination of the pre-training CNN, and localization and classification have different feature preferences [38, 34, 29].

Fig. 4 plots the AP$_{50}$ learning curves of four different pre-training models and DETR, where the models in Fig. 4 correspond to the models in Table 4 one-to-one. As shown in Fig. 4, model (d) UP-DETR achieves faster convergence at the early training stage with feature reconstruction. The experiments suggest that random query patch detection is complementary to the contrastive learning for a better visual representation. The former is designed for the spatial localization with position embeddings, and the latter is designed for instance or cluster classification.

4.3.3 Attention Mask

After downstream task fine-tuning, we find that there is no noticeable difference between the UP-DETR pre-trained with and without attention mask. Instead of the fine-tuning result, we plot the loss curves in the pretext task to illustrate the effectiveness of attention mask.

As shown in Fig. 6, at the early training stage, UP-DETR without attention mask has a lower loss. However, as the model converging, UP-DETR with attention mask takes over with a lower loss. The curves seem weird at the first glance, but it is reasonable because the loss is calculated by the optimal bipartite matching. During the early training stage, the model is not converged, and the model without attention mask takes more object queries into attention. Intuitively, the model is easier to be optimized due to introducing more object queries. However, there is a mismatching between the query patch and the ground truth for the model without attention mask. As the model converging, the attention mask gradually takes effect, which masks
Figure 5: The unsupervised localization of patch queries with UP-DETR. The first line is the original image with predicted bounding boxes. The second line is query patches cropped from the original image with data augmentation. The value in the upper left corner of the bounding box is the model confidence.

As shown in Fig. 5, unsupervisedly pre-trained with random query patch detection, UP-DETR successfully learns to locate the bounding box of given query patches and suppress the duplicated bounding boxes. It suggests that UP-DETR with random query patch detection is effective to learns the ability of object localization, which helps the downstream transfer learning.

5. Conclusion

We present a novel pretext task called random query patch detection to unsupervisedly pre-train the transformers in DETR. With unsupervised pre-training, UP-DETR significantly outperforms DETR by a large margin with higher precision and much faster convergence on PASCAL VOC. For the challenging COCO dataset with sufficient training data, UP-DETR still surpasses DETR even with a long training schedule. It indicates that pre-training transformers is indispensable for different scale of training data in object detection.

From the perspective of unsupervised pre-training models, pre-training CNN backbone and pre-training transformers are separated now. Recent studies of unsupervised pre-training mainly focus on feature discrimination with contrastive learning instead of specialized modules for spatial localization. But in UP-DETR pre-training, the pretext task is mainly designed for patch localization by positional encodings and learn-able object queries. We hope an advanced method can integrate CNN and transformers pre-training into a unified end-to-end framework and apply UP-DETR to more downstream tasks (e.g. few-shot object detection and object tracking).
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