

# DiffusionDet: Diffusion Model for Object Detection

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## Abstract

We propose *DiffusionDet*, a new framework that formulates object detection as a denoising diffusion process from noisy boxes to object boxes. During training stage, object boxes diffuse from ground-truth boxes to random distribution, and the model learns to reverse this noising process. In inference, the model refines a set of randomly generated boxes to the output results in a progressive way. The extensive evaluations on the standard benchmarks, including MS-COCO and LVIS, show that *DiffusionDet* achieves favorable performance compared to previous well-established detectors. Our work brings two important findings in object detection. First, random boxes, although drastically different from pre-defined anchors or learned queries, are also effective object candidates. Second, object detection, one of the representative perception tasks, can be solved by a generative way. Our code is available at <https://github.com/ShoufaChen/DiffusionDet>.

## 1. Introduction

Object detection aims to predict a set of bounding boxes and associated category labels for targeted objects in one image. As a fundamental visual recognition task, it has become the cornerstone of many related recognition scenarios, such as instance segmentation [33, 48], pose estimation [9, 20], action recognition [29, 73], object tracking [41, 58], and visual relationship detection [40, 56].

Modern object detection approaches have been evolving with the development of object candidates, *i.e.*, from empirical object priors [24, 53, 64, 66] to learnable object queries [10, 81, 102]). Specifically, the majority of detectors solve detection tasks by defining surrogate regression and classification on empirically designed object candidates, such as sliding windows [25, 71], region proposals [24, 66], anchor boxes [50, 64] and reference points [17, 97, 101]. Recently, DETR [10] proposes learnable object queries to eliminate the hand-designed components and set up an end-to-end detection pipeline, attracting great attention on query-based detection paradigm [21, 46, 81, 102].

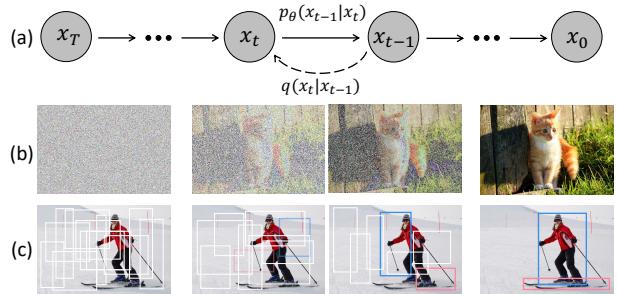
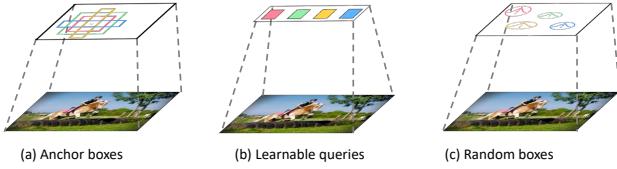


Figure 1. **Diffusion model for object detection.** (a) A diffusion model where  $q$  is the diffusion process and  $p_\theta$  is the reverse process. (b) Diffusion model for image generation task. (c) We propose to formulate object detection as a denoising diffusion process from noisy boxes to object boxes.

While these works achieve a simple and effective design, they still have a dependency on a fixed set of learnable queries. A natural question is: *is there a simpler approach that does not even need the surrogate of learnable queries?*

We answer this question by designing a novel framework that directly detects objects from a set of random boxes. Starting from purely random boxes, which do not contain learnable parameters that need to be optimized in training, we expect to gradually refine the positions and sizes of these boxes until they perfectly cover the targeted objects. This *noise-to-box* approach does not require heuristic object priors nor learnable queries, further simplifying the object candidates and pushing the development of the detection pipeline forward.

Our motivation is illustrated in Figure 1. We think of the philosophy of noise-to-box paradigm is analogous to *noise-to-image* process in the denoising diffusion models [15, 35, 79], which are a class of likelihood-based models to generate the image by gradually removing noise from an image via the learned denoising model. Diffusion models have achieved great success in many generation tasks [3, 4, 37, 63, 85] and start to be explored in perception tasks like image segmentation [1, 5, 6, 12, 28, 42, 89]. However, to the best of our knowledge, there is no prior arts that successfully adopt it to object detection.



**Figure 2. Comparisons of different object detection paradigms.** (a) Detection from empirical object priors [64, 66]; (b) Detection from learnable queries [10, 81, 102]; (c) Detection from random boxes (**Ours**).

In this work, we propose DiffusionDet, which tackles the object detection task with a diffusion model by casting detection as a generative task over the space of the positions (center coordinates) and sizes (widths and heights) of bounding boxes in the image. At training stage, Gaussian noise controlled by a variance schedule [35] is added to ground truth boxes to obtain *noisy* boxes. Then these noisy boxes are used to crop [33, 66] features of Region of Interest (RoI) from the output feature map of the backbone encoder, *e.g.*, ResNet [34], Swin Transformer [54]. Finally, these RoI features are sent to the detection decoder, which is trained to predict the ground-truth boxes without noise. With this training objective, DiffusionDet is able to predict the ground truth boxes from random boxes. At inference stage, DiffusionDet generates bounding boxes by reversing the learned diffusion process, which adjusts a noisy prior distribution to the learned distribution over bounding boxes.

The noise-to-box pipeline of DiffusionDet has the appealing advantage of Once-for-All: we can train the network once and use the same network parameters under diverse settings in inference. (1) *Dynamic boxes*: Leveraging random boxes as object candidates, DiffusionDet decouples the training and evaluation. DiffusionDet can be trained with  $N_{train}$  random boxes while being evaluated with  $N_{eval}$  random boxes, where the  $N_{eval}$  is arbitrary and does not need to be equal to  $N_{train}$ . (2) *Progressive refinement*: The diffusion model benefits DiffusionDet by iterative refinement. We can adjust the number of denoising sampling steps to improve the detection accuracy or accelerate the inference speed. This flexibility enables DiffusionDet to suit different detection scenarios where accuracy and speed are required differently.

We evaluate DiffusionDet on MS-COCO [51] dataset. With ResNet-50 [34] backbone, DiffusionDet achieves 45.5 AP using a single sampling step, which significantly outperforms Faster R-CNN [66] (40.2 AP), DETR [10] (42.0 AP) and on par with Sparse R-CNN [81] (45.0 AP). Besides, we can further improve DiffusionDet up to 46.2 AP by increasing the number of sampling steps. On the contrary, existing approaches [10, 81, 102] do not have this refinement property and would have a remarkable performance drop when evaluated in an iterative way. Moreover, we further conduct experiments on challenging LVIS [31] dataset, and

DiffusionDet also performs well on this long-tailed dataset, achieving 42.1 AP with Swin-Base [54] backbone.

Our **contributions** are summarized as follows:

- We formulate object detection as a generative denoising process, which is the first study to apply the diffusion model to object detection to the best of our knowledge.
- Our noise-to-box detection paradigm has several appealing properties, such as decoupling training and evaluation stage for dynamic boxes and progressive refinement.
- We conduct extensive experiments on MS-COCO and LVIS benchmarks. DiffusionDet achieves favorable performance against previous well-established detectors.

## 2. Related Work

**Object detection.** Most modern object detection approaches perform box regression and category classification on empirical object priors, such as proposals [24, 66], anchors [50, 64, 65], points [84, 87, 101]. Recently, Carion *et al.* proposed DETR [10] to detect objects using a fixed set of learnable queries. Since then, the query-based detection paradigm has attracted great attention and inspired a series of following works [46, 52, 57, 80, 81, 102]. In this work, we push forward the development of the object detection pipeline further with DiffusionDet, as compared in Figure 2.

**Diffusion model.** As a class of deep generative models, diffusion models [35, 77, 79] start from the sample in random distribution and recover the data sample via a gradual denoising process. Diffusion models have recently demonstrated remarkable results in fields including computer vision [4, 19, 30, 32, 36, 60, 63, 68, 69, 74, 96, 99], nature language processing [3, 27, 47], audio processing [38, 43, 45, 62, 82, 92, 95], interdisciplinary applications [2, 37, 39, 70, 85, 91, 94], etc. More applications of diffusion models can be found in recent surveys [8, 96].

**Diffusion model for perception tasks.** While Diffusion models have achieved great success in image generation [15, 35, 79], their potential for discriminative tasks has yet to be fully explored. Some pioneer works tried to adopt the diffusion model for image segmentation tasks [1, 5, 6, 12, 28, 42, 89], for example, Chen *et al.* [12] adopted Bit Diffusion model [13] for panoptic segmentation [44] of images and videos. However, despite significant interest in this idea, there are no previous solutions that successfully adapt generative diffusion models for object detection, the progress of which remarkably lags behind that of segmentation. We argue that this may be because segmentation tasks are processed in an image-to-image style, which is more conceptually similar to the image generation tasks, while object detection is a set prediction problem [10] which requires assigning object candidates [10, 49, 66] to ground truth objects. To the best of our knowledge, this is the first work that adopts a diffusion model for object detection.

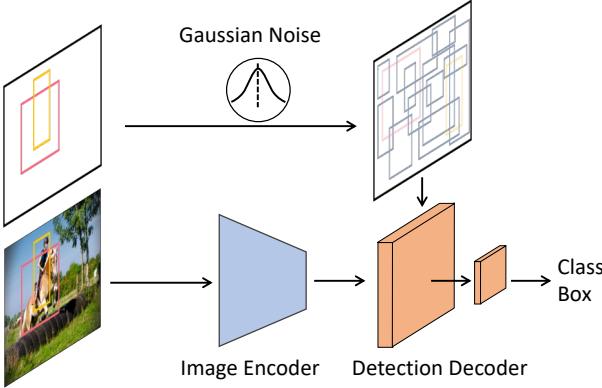


Figure 3. **DiffusionDet framework.** The image encoder extracts feature representation from an input image. The detection decoder takes noisy boxes as input and predicts category classification and box coordinates. During training, the noisy boxes are constructed by adding Gaussian noise to ground-truth boxes. In inference, the noisy boxes are randomly sampled from the Gaussian distribution.

### 3. Approach

#### 3.1. Preliminaries

**Object detection.** The learning objective of object detection is input-target pairs  $(\mathbf{x}, \mathbf{b}, \mathbf{c})$ , where  $\mathbf{x}$  is the input image,  $\mathbf{b}$  and  $\mathbf{c}$  are a set of bounding boxes and category labels for objects in the image  $\mathbf{x}$ , respectively. More specifically, we formulate the  $i$ -th box in the set as  $\mathbf{b}^i = (c_x^i, c_y^i, w^i, h^i)$ , where  $(c_x^i, c_y^i)$  is the center coordinates of the bounding box,  $(w^i, h^i)$  are width and height of that bounding box, respectively.

**Diffusion model.** Diffusion models [35, 75–77] are a class of likelihood-based models inspired by nonequilibrium thermodynamics [77, 78]. These models define a Markovian chain of diffusion forward process by gradually adding noise to sample data. The forward noise process is defined as

$$q(\mathbf{z}_t | \mathbf{z}_0) = \mathcal{N}(\mathbf{z}_t | \sqrt{\bar{\alpha}_t} \mathbf{z}_0, (1 - \bar{\alpha}_t) \mathbf{I}), \quad (1)$$

which transforms data sample  $\mathbf{z}_0$  to a latent noisy sample  $\mathbf{z}_t$  for  $t \in \{0, 1, \dots, T\}$  by adding noise to  $\mathbf{z}_0$ .  $\bar{\alpha}_t := \prod_{s=0}^t \alpha_s = \prod_{s=0}^t (1 - \beta_s)$  and  $\beta_s$  represents the noise variance schedule [35]. During training, a neural network  $f_\theta(\mathbf{z}_t, t)$  is trained to predict  $\mathbf{z}_0$  from  $\mathbf{z}_t$  by minimizing the training objective with  $\ell_2$  loss [35]:

$$\mathcal{L}_{\text{train}} = \frac{1}{2} \|f_\theta(\mathbf{z}_t, t) - \mathbf{z}_0\|^2. \quad (2)$$

At inference stage, data sample  $\mathbf{z}_0$  is reconstructed from noise  $\mathbf{z}_T$  with the model  $f_\theta$  and an updating rule [35, 76] in an iterative way, i.e.,  $\mathbf{z}_T \rightarrow \mathbf{z}_{T-\Delta} \rightarrow \dots \rightarrow \mathbf{z}_0$ . More

detailed formulation of diffusion models can be found in Appendix A.

In this work, we aim to solve the object detection task via the diffusion model. In our setting, data samples are a set of bounding boxes  $\mathbf{z}_0 = \mathbf{b}$ , where  $\mathbf{b} \in \mathbb{R}^{N \times 4}$  is a set of  $N$  boxes. A neural network  $f_\theta(\mathbf{z}_t, t, \mathbf{x})$  is trained to predict  $\mathbf{z}_0$  from noisy boxes  $\mathbf{z}_t$ , conditioned on the corresponding image  $\mathbf{x}$ . The corresponding category label  $\mathbf{c}$  is produced accordingly.

#### 3.2. Architecture

Since the diffusion model generates data samples iteratively, it needs to run model  $f_\theta$  multiple times at the inference stage. However, it would be computationally intractable to directly apply  $f_\theta$  on the raw image at every iterative step. Therefore, we propose to separate the whole model into two parts, *image encoder* and *detection decoder*, where the former runs only once to extract a deep feature representation from the raw input image  $\mathbf{x}$ , and the latter takes this deep feature as condition, instead of the raw image, to progressively refine the box predictions from noisy boxes  $\mathbf{z}_t$ .

**Image encoder.** Image encoder takes as input the raw image and extracts its high-level features for the following detection decoder. We implement DiffusionDet with both Convolutional Neural Networks such as ResNet [34] and Transformer-based models like Swin [54]. Feature Pyramid Network [49] is used to generate multi-scale feature maps for both ResNet and Swin backbones following [49, 54, 81].

**Detection decoder.** Borrowed from Sparse R-CNN [81], the detection decoder takes as input a set of proposal boxes to crop ROI-feature [33, 66] from feature map generated by image encoder, and sends these ROI-features to detection head to obtain box regression and classification results. Following [10, 81, 102], our detection decoder is composed of 6 cascading stages. The differences between our decoder and the one in Sparse R-CNN are that (1) DiffusionDet begins from random boxes while Sparse R-CNN uses a fixed set of learned boxes in inference; (2) Sparse R-CNN takes as input pairs of the proposal boxes and its corresponding proposal feature, while DiffusionDet needs the proposal boxes only; (3) DiffusionDet re-uses the detector head in iterative sampling steps and the parameters are shared across different steps, each of which is specified to the diffusion process by timestep embedding [35, 86], while Sparse R-CNN uses the detection decoder only once in the forward pass.

#### 3.3. Training

During training, we first construct the diffusion process from ground-truth boxes to noisy boxes and then train the model to reverse this process. Algorithm 1 provides the pseudo-code of DiffusionDet training procedure.

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**Algorithm 1** DiffusionDet Training

---

```
def train_loss(images, gt_boxes):
    """
    images: [B, H, W, 3]
    gt_boxes: [B, *, 4]
    # B: batch
    # N: number of proposal boxes
    """

    # Encode image features
    feats = image_encoder(images)

    # Pad gt_boxes to N
    pb = pad_boxes(gt_boxes) # padded boxes: [B, N, 4]

    # Signal scaling
    pb = (pb * 2 - 1) * scale

    # Corrupt gt_boxes
    t = randint(0, T) # time step
    eps = normal(mean=0, std=1) # noise: [B, N, 4]
    pb_crpt = sqrt(alpha_cumprod(t)) * pb +
        sqrt(1 - alpha_cumprod(t)) * eps

    # Predict
    pb_pred = detection_decoder(pb_crpt, feats, t)

    # Set prediction loss
    loss = set_prediction_loss(pb_pred, gt_boxes)

    return loss
```

alpha\_cumprod(t): cumulative product of  $\alpha_i$ , i.e.,  $\prod_{i=1}^t \alpha_i$

---

**Ground truth boxes padding.** For modern object detection benchmarks [18, 31, 51, 72], the number of instances of interest typically varies across images. Therefore, we first *pad* some extra boxes to original ground truth boxes such that all boxes are summed up to a fixed number  $N_{train}$ . We explore several padding strategies, for example, repeating existing ground truth boxes, concatenating random boxes or image-size boxes. Comparisons of these strategies are in Section 4.4, and concatenating random boxes works best.

**Box corruption.** We add Gaussian noises to the padded ground truth boxes. The noise scale is controlled by  $\alpha_t$  (in Eq. (1)), which adopts the monotonically decreasing cosine schedule for  $\alpha_t$  in different time step  $t$ , as proposed in [59]. Notably, the ground truth box coordinates need to be scaled as well since the signal-to-noise ratio has a significant effect on the performance of diffusion model [12]. We observe that object detection favors a relatively higher signal scaling value than image generation task [13, 15, 35]. More discussions are in Section 4.4.

**Training losses.** The detection detector takes as input  $N_{train}$  corrupted boxes and predicts  $N_{train}$  predictions of category classification and box coordinates. We apply set prediction loss [10, 81, 102] on the set of  $N_{train}$  predictions. We assign multiple predictions to each ground truth by selecting the top  $k$  predictions with the least cost by an optimal transport assignment method [16, 22, 23, 90].

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**Algorithm 2** DiffusionDet Sampling

---

```
def infer(images, steps, T):
    """
    images: [B, H, W, 3]
    # steps: number of sample steps
    # T: number of time steps
    """

    # Encode image features
    feats = image_encoder(images)

    # noisy boxes: [B, N, 4]
    pb_t = normal(mean=0, std=1)

    # uniform sample step size
    times = reversed(linespace(-1, T, steps))

    # [(T-1, T-2), (T-2, T-3), ..., (1, 0), (0, -1)]
    time_pairs = list(zip(times[:-1], times[1:]))

    for t_now, t_next in zip(time_pairs):
        # Predict pb_0 from pb_t
        pb_pred = detection_decoder(pb_t, feats, t_now)

        # Estimate pb_t at t_next
        pb_t = ddim_step(pb_t, pb_pred, t_now, t_next)

        # Box renewal
        pb_t = box_renewal(pb_t)

    return pb_pred
```

linespace: generate evenly spaced values

---

### 3.4. Inference

The inference procedure of DiffusionDet is a denoising sampling process from noise to object boxes. Starting from boxes sampled in Gaussian distribution, the model progressively refines its predictions, as shown in Algorithm 2.

**Sampling step.** In each sampling step, the random boxes or the estimated boxes from the last sampling step are sent into the detection decoder to predict the category classification and box coordinates. After obtaining the boxes of the current step, DDIM [76] is adopted to estimate the boxes for the next step. We note that sending the predicted boxes without DDIM to the next step is also an optional progressive refinement strategy. However, it brings significant deterioration, as discussed in Section 4.4.

**Box renewal.** After each sampling step, the predicted boxes can be coarsely categorized into two types, *desired* and *undesired* predictions. The desired predictions contain boxes that are properly located at corresponding objects, while the undesired ones are distributed arbitrarily. Directly sending these undesired boxes to the next sampling iteration would not bring a benefit since their distribution is not constructed by box corruption in training. To make inference better align with training, we propose the strategy of *box renewal* to revive these undesired boxes by replacing them with random boxes. Specifically, we first filter out undesired boxes with scores lower than a particular threshold. Then, we concatenate the remaining boxes with new random boxes sampled from a Gaussian distribution.

**Once-for-all.** Thanks to the random boxes design, we can evaluate DiffusionDet with an arbitrary number of random boxes and the number of sampling steps, which do not need to be equal to the training stage. As a comparison, previous approaches [10, 81, 102] rely on the same number of processed boxes during training and evaluation, and their detection decoders are used only once in the forward pass.

## 4. Experiments

We first show the once-for-all property of DiffusionDet. Then we compare DiffusionDet with previous well-established detectors on MS-COCO [51] and LVIS [31] dataset. Finally, we provide ablation studies on the components of DiffusionDet.

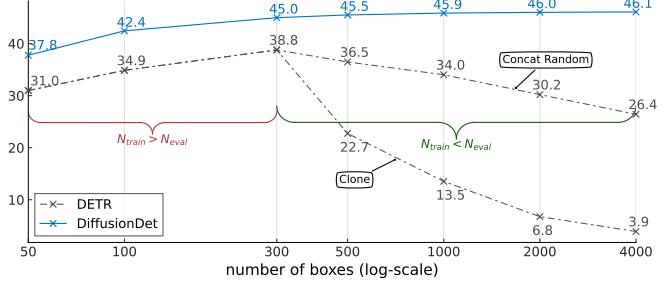
**MS-COCO** [51] dataset contains about 118K training images in the `train2017` set and 5K validation images in the `val2017` set. There are 80 object categories in total. We report box average precision over multiple IoU thresholds (AP), threshold 0.5 (AP<sub>50</sub>) and 0.75 (AP<sub>75</sub>).

**LVIS v1.0** [31] dataset is a large-vocabulary object detection and instance segmentation dataset which has 100K training images and 20K validation images. LVIS shares the same source images as MS-COCO, while its annotations capture the long-tailed distribution in 1203 categories. We adopt MS-COCO style box metric AP, AP<sub>50</sub> and AP<sub>75</sub> in LVIS evaluation.

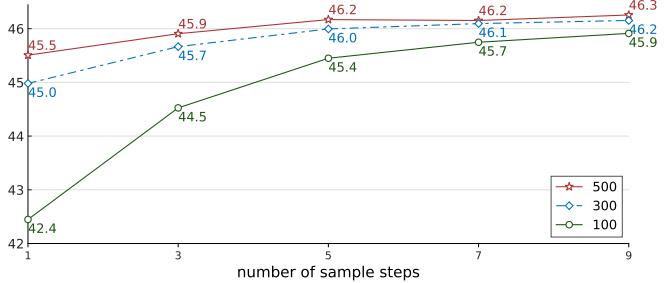
### 4.1. Implementation Details.

**Training schedules.** The ResNet and Swin backbone are initialized with pre-trained weights on ImageNet-1K and ImageNet-21K [14], respectively. The newly added detection decoder is initialized with Xavier init [26]. We train DiffusionDet using AdamW [55] optimizer with the initial learning rate as  $2.5 \times 10^{-5}$  and the weight decay as  $10^{-4}$ . All models are trained with a mini-batch size 16 on 8 GPUs. For MS-COCO, the default training schedule is 450K iterations, with the learning rate divided by 10 at 350K and 420K iterations. For LVIS, the training schedule is 210K, 250K, 270K. Data augmentation strategies contain random horizontal flip, scale jitter of resizing the input images such that the shortest side is at least 480 and at most 800 pixels while the longest is at most 1333 [93], and random crop augmentations. We do not use the EMA and some strong data augmentation like MixUp [98] or Mosaic [23].

**Inference details.** At the inference stage, the detection decoder iteratively refines the predictions from Gaussian random boxes. We select top-100 and top-300 scoring predictions for MS-COCO and LVIS, respectively. The predictions at each sampling step are ensembled together by NMS to get the final predictions.



(a) **Dynamic boxes.** Both DETR and DiffusionDet are trained with 300 object queries or proposal boxes. More proposal boxes in inference bring accuracy improvement on DiffusionDet, while degenerate DETR.



(b) **Progressive refinement.** DiffusionDet is trained with 300 proposal boxes and evaluated with different numbers of proposal boxes. For all cases, the accuracy increases with refinement times.

Figure 4. **Once-for-all properties of DiffusionDet.** All experiments are trained on COCO 2017 `train` set and evaluated on COCO 2017 `val` set. DiffusionDet uses the same network parameters for all settings in Figure 4a and 4b. Our proposed DiffusionDet is able to benefit from more proposal boxes and iterative refinements using the same network parameters.

### 4.2. Main Properties

The main properties of DiffusionDet lie on *once training for all inference cases*. Once the model is trained, it can be used with changing the number of boxes and number of sample steps in inference, as shown in Figure 4. DiffusionDet can achieve better accuracy by using more boxes or/and more refining steps at the cost of higher latency. Therefore, we can deploy a single DiffusionDet to multiple scenarios and obtain a desired speed-accuracy trade-off without re-training the network.

**Dynamic boxes.** We compare DiffusionDet with DETR [10] to show the advantage of dynamic boxes. Comparisons with other detectors are in Appendix B. We reproduce DETR [10] with 300 object queries using the official code and default settings for 300 epochs training. We train DiffusionDet with 300 random boxes such that the number of candidates is consistent with DETR for a fair comparison. The evaluation is on {50, 100, 300, 500, 1000, 2000, 4000} queries or boxes.

Method	AP	AP <sub>50</sub>	AP <sub>75</sub>	AP <sub>s</sub>	AP <sub>m</sub>	AP <sub>l</sub>
ResNet-50 [34]						
RetinaNet [93]	38.7	58.0	41.5	23.3	42.3	50.3
Faster R-CNN [93]	40.2	61.0	43.8	24.2	43.5	52.0
Cascade R-CNN [93]	44.3	62.2	48.0	26.6	47.7	57.7
DETR [10]	42.0	62.4	44.2	20.5	45.8	61.1
Deformable DETR [102]	43.8	62.6	47.7	26.4	47.1	58.0
Sparse R-CNN [81]	45.0	63.4	48.2	26.9	47.2	59.5
DiffusionDet (1 step)	45.5	65.1	48.7	27.5	48.1	61.2
DiffusionDet (4 step)	46.1	66.0	49.2	28.6	48.5	61.3
DiffusionDet (8 step)	<b>46.2</b>	<b>66.4</b>	<b>49.5</b>	<b>28.7</b>	<b>48.5</b>	<b>61.5</b>
ResNet-101 [34]						
RetinaNet [93]	40.4	60.2	43.2	24.0	44.3	52.2
Faster R-CNN [93]	42.0	62.5	45.9	25.2	45.6	54.6
Cascade R-CNN [11]	45.5	63.7	49.9	27.6	49.2	59.1
DETR [10]	43.5	63.8	46.4	21.9	48.0	61.8
Sparse R-CNN [81]	46.4	64.6	49.5	28.3	48.3	61.6
DiffusionDet (1 step)	46.6	66.3	50.0	30.0	49.3	62.8
DiffusionDet (4 step)	46.9	66.8	50.4	<b>30.6</b>	49.5	62.6
DiffusionDet (8 step)	<b>47.1</b>	<b>67.1</b>	<b>50.6</b>	30.2	<b>49.8</b>	<b>62.7</b>
Swin-Base [54]						
Cascade R-CNN [54]	51.9	70.9	56.5	35.4	55.2	67.4
Sparse R-CNN	52.0	72.2	57.0	35.8	55.1	68.2
DiffusionDet (1 step)	52.3	72.7	56.3	34.8	56.0	68.5
DiffusionDet (4 step)	52.7	73.5	56.8	36.1	56.0	<b>68.9</b>
DiffusionDet (8 step)	<b>52.8</b>	<b>73.6</b>	<b>56.8</b>	<b>36.1</b>	<b>56.2</b>	68.8

Table 1. Comparisons with different object detectors on COCO 2017 **val** set. The reference after each method indicates the source of its results. The method without reference is our implementation.

Since the learnable queries are fixed after training in the original setting of DETR, we propose a simple workaround to enable DETR work with different number of queries: when  $N_{eval} < N_{train}$ , we directly choose  $N_{eval}$  queries from  $N_{train}$  queries; when  $N_{eval} > N_{train}$ , we concatenate extra  $N_{eval} - N_{train}$  randomly initialized queries (a.k.a. concat random). We present results in Figure 4a. The performance of DiffusionDet increases steadily with the number of boxes used for evaluation. On the contrary, DETR has a clear performance drop when the  $N_{eval}$  is different with  $N_{train}$ , i.e., 300. Besides, this performance drop becomes larger when the difference between  $N_{eval}$  and  $N_{train}$  increases. For example, when the number of boxes increases to 4000, DETR only has 26.4 AP with concat random strategy, which is 12.4 lower than the peak value (i.e., 38.8 AP with 300 queries). As a comparison, DiffusionDet can achieve 1.1 AP gain with 4000 boxes.

We also implement another method for DETR when  $N_{eval} > N_{train}$ , cloning existing  $N_{train}$  queries up to  $N_{eval}$  (a.k.a. clone). We observe that concat random strategy consistently performs better than the clone. It is reasonable because the cloned queries will produce similar detection results as the original queries. In contrast, random queries introduce more diversity to the detection results.

Method	AP	AP <sub>50</sub>	AP <sub>75</sub>	AP <sub>s</sub>	AP <sub>m</sub>	AP <sub>l</sub>	AP <sub>r</sub>	AP <sub>c</sub>	AP <sub>f</sub>
ResNet-50 [34]									
Faster R-CNN <sup>†</sup>	22.5	37.1	23.6	16.5	29.6	34.9	9.9	21.1	29.7
Cascade R-CNN <sup>†</sup>	26.3	37.8	27.8	18.4	34.4	41.9	12.3	24.9	34.1
Faster R-CNN	25.2	40.6	26.9	18.5	32.2	37.7	16.4	23.4	31.1
Cascade R-CNN	29.4	41.4	30.9	20.6	37.5	44.3	20.0	27.7	35.4
Sparse R-CNN	29.2	41.0	30.7	20.7	36.9	44.2	20.6	27.7	34.6
DiffusionDet (1 step)	30.4	42.8	31.8	20.6	38.6	47.6	23.5	28.1	36.0
DiffusionDet-(4 step)	31.8	45.0	33.2	22.5	39.9	48.3	24.8	29.3	37.6
DiffusionDet-(8 step)	<b>31.9</b>	<b>45.3</b>	<b>33.1</b>	<b>22.8</b>	<b>40.2</b>	<b>48.1</b>	<b>24.0</b>	<b>29.5</b>	<b>38.1</b>
ResNet-101 [34]									
Faster R-CNN <sup>†</sup>	24.8	39.8	26.1	17.9	32.2	36.9	13.7	23.1	31.5
Cascade R-CNN <sup>†</sup>	28.6	40.1	30.1	19.8	37.1	43.8	15.3	27.3	35.9
Faster R-CNN	27.2	42.9	29.1	20.3	35.0	40.4	18.8	25.4	33.0
Cascade R-CNN	31.6	43.8	33.4	22.3	39.7	47.3	23.9	29.8	37.0
Sparse R-CNN	30.1	42.0	31.9	21.3	38.5	45.6	23.5	27.5	35.9
DiffusionDet (1 step)	31.9	44.6	33.1	21.6	40.3	49.0	23.4	30.5	37.1
DiffusionDet-(4 step)	32.9	46.5	34.3	23.3	41.1	49.9	24.2	31.3	38.6
DiffusionDet-(8 step)	<b>33.5</b>	<b>47.3</b>	<b>34.7</b>	<b>23.6</b>	<b>41.9</b>	<b>49.8</b>	<b>24.8</b>	<b>32.0</b>	<b>39.0</b>
Swin-Base [54]									
DiffusionDet-(1 step)	40.6	54.8	42.7	28.3	50.0	61.6	33.6	39.8	44.6
DiffusionDet-(4 step)	41.9	57.1	44.0	30.3	50.6	62.3	34.9	40.7	46.3
DiffusionDet-(8 step)	<b>42.1</b>	<b>57.8</b>	<b>44.3</b>	<b>31.0</b>	<b>51.3</b>	<b>62.5</b>	<b>34.3</b>	<b>41.0</b>	<b>46.7</b>

Table 2. Comparisons with different object detectors on LVIS v1.0 **val** set. We re-implement all detectors using federated loss [100] except for the rows in light gray (with <sup>†</sup>).

**Progressive refinement.** The performance of DiffusionDet can be improved not only by increasing the number of random boxes but by iterating more steps. We evaluate DiffusionDet with 100, 300, and 500 random boxes by increasing their iterative steps from 1 to 9. The results are presented in Figure 4b. We see that DiffusionDet with these three settings all have steady performance gains with more refining steps. Besides, DiffusionDet with fewer random boxes tends to have a larger gain with refinement. For example, the AP of DiffusionDet instance with 100 random boxes increases from 42.4 (1 step) to 45.9 (9 steps), an absolute 3.5 AP improvement. This accuracy performance is comparable with 45.0 (1 step) of 300 random boxes and 45.5 (1 step) of 500, showing that high accuracy in DiffusionDet could be achieved by either increasing the number of proposal boxes or the iterative steps.

In comparison, we find that previous approaches [10, 81, 102] do not have this refinement property. They can use the detection decoder only once. Using two or more iteration steps will drop the performance. More detailed comparison can be found in Appendix C.

### 4.3. Benchmarking on Detection Datasets

We compare DiffusionDet with previous detectors [7, 10, 50, 66, 81, 102] on MS-COCO and LVIS dataset. We adopt 500 boxes for both training and inference in this subsection. More detailed experimental settings are in Appendix D.

scale	AP	AP <sub>50</sub>	AP <sub>75</sub>
0.1	38.5	54.2	41.4
1.0	44.3	63.2	47.6
2.0	45.0	64.3	48.1
3.0	44.8	63.9	48.2

(a) **Signal scale.** A large scaling factor can improve detection performance.

case	AP	AP <sub>50</sub>	AP <sub>75</sub>
Repeat	43.7	62.6	47.0
Cat Gaussian	45.0	64.3	48.1
Cat Uniform	44.7	63.7	48.3
Cat Full	44.8	63.9	47.9

(b) **GT boxes padding.** Concatenating Gaussian boxes works best.

score thresh.	AP	AP <sub>50</sub>	AP <sub>75</sub>
0.0	45.4	65.2	48.8
0.3	45.9	65.7	49.2
0.5	46.2	66.1	49.4
0.7	46.0	66.2	49.0

(d) **Box renewal** at evaluation of step 8. The threshold of 0.5 works best.

eval \ train	100	300	500
100	42.5	42.4	41.1
300	43.8	45.0	44.8
500	44.2	45.5	45.6
1000	44.5	45.9	46.1

(e) **Matching between  $N_{train}$  and  $N_{eval}$ .** The best for each row is underlined.

DDIM	box renewal	step 1	step 4	step 8
		45.0	43.4	43.4
✓		45.0	45.5	45.4
	✓	45.0	45.6	45.6
✓	✓	45.0	45.8	46.2

(c) **Sampling strategy.** Using both DDIM and box renewal works best.

# boxes	step	AP	AP <sub>50</sub>	AP <sub>75</sub>	FPS
[81]	1	45.0	63.4	48.2	31.4
100	1	42.5	60.3	45.9	31.6
300	1	45.0	64.3	48.1	31.3
300	4	45.8	65.7	49.2	12.4

(f) **Accuracy vs. speed.** Using more boxes bring performance gain at the cost of latency.

Table 3. **DiffusionDet ablation experiments** on MS-COCO. We report AP, AP<sub>50</sub>, and AP<sub>75</sub>. If not specified, the default setting is: the backbone is ResNet-50 [34] with FPN [49], the signal scale is 2.0, ground-truth boxes padding method is concatenating Gaussian random boxes, DDIM and box renewal are used in sampling step, where the score threshold in box renewal is 0.5, both training and evaluation use 300 boxes. Default settings are marked in gray .

**MS-COCO.** In Table 1 we compare the object detection performance of DiffusionDet with previous detectors on MS-COCO. DiffusionDet without refinement (*i.e.*, step 1) achieves 45.5 AP with ResNet-50 backbone, outperforming well-established methods such as Faster R-CNN, RetinaNet, DETR and Sparse R-CNN by a non-trivial margin. Besides, DiffusionDet can make its superiority more remarkable when using more iterative refinements. For example, when using ResNet-50 as the backbone, DiffusionDet outperforms Sparse R-CNN by 0.5 AP (45.5 vs. 45.0) with a single step while by 1.2 AP (46.2 vs. 45.0) with 8 steps.

DiffusionDet shows steady improvement when the backbone size scales up. DiffusionDet with ResNet-101 achieves 46.6 AP (1 step) and 47.1 AP (8 steps). When using ImageNet-21k pre-trained Swin-Base [54] as the backbone, DiffusionDet obtains 52.3 AP for a single step and 52.8 AP with 8 steps, outperforming strong baselines such as Cascade R-CNN and Sparse R-CNN.

**LVIS v1.0.** We compare the results on a more challenging LVIS dataset in Table 2. We reproduce Faster R-CNN and Cascade R-CNN based on detectron2 [93] while Sparse R-CNN on its original code. We first reproduce Faster R-CNN and Cascade R-CNN using the default settings of detectron2, achieving 22.5/24.8 and 26.3/28.8 AP (with <sup>†</sup> in Table 2) with ResNet-50/101 backbone, respectively. Further, we boost their performance using the federated loss in [100]. Since images in LVIS are annotated in a federated way [31], the negative categories are sparsely annotated, which deteriorates the training gradients, especially for rare classes [83]. Federated loss is proposed to mitigate this issue by sampling a subset  $S$  of classes for each training image that includes all positive annotations and a random subset of negative ones. Following [100], we

choose  $|S| = 50$  in all experiments. Faster R-CNN and Cascade R-CNN earn about 3 AP gains with federated loss. All following comparisons are based on this loss.

We see that DiffusionDet attains remarkable gains using more refinement steps, with both small and large backbones. Moreover, we note that refinement brings more gains on LVIS compared with MS-COCO. For example, its performance increases from 45.5 to 46.2 (+ 0.7 AP) on MS-COCO while from 30.4 to 31.9 (+1.5 AP) on LVIS, which demonstrates that our refining strategy would become more helpful for a more challenging benchmark.

#### 4.4. Ablation Study

We conduct ablation experiments on MS-COCO to study DiffusionDet in detail. All experiments use ResNet-50 with FPN as the backbone and 300 boxes for training and inference without further specification.

**Signal scaling.** The signal scaling factor controls the signal-to-noise ratio (SNR) of the diffusion process. We study the influence of scaling factors in Table 3a. Results demonstrate that the scaling factor of 2.0 achieves optimal AP performance, outperforming the standard value of 1.0 in image generation task [13, 35] and 0.1 used for panoptic segmentation [12]. We explain that it is because one box only has four representation parameters, *i.e.*, center coordinates ( $c_x, c_y$ ) and box size ( $w, h$ ), which is coarsely analogous to an image with only four pixels in image generation. The box representation is more fragile than the dense representation, *e.g.*, 512 × 512 mask presentation in panoptic segmentation [13]. Therefore, DiffusionDet prefers an easier training objective with an increased signal-to-noise ratio compared to image generation and panoptic segmentation.

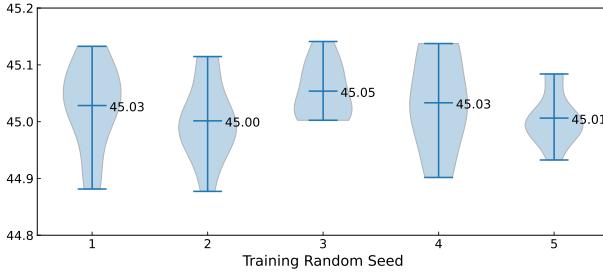


Figure 5. **Statistical results** over 5 independent training instances, each is evaluated 10 times with different random seeds. The number in the figure shows mean values.

**GT boxes padding strategy.** As introduced in Section 3.3, we need to *pad* additional boxes to the original ground truth boxes such that each image has the same number of boxes. We study different padding strategies in Table 3b, including (1.) repeating original ground truth boxes evenly until the total number reaches pre-defined value  $N_{train}$ ; (2.) padding random boxes that follow Gaussian distribution; (3.) padding random boxes that follow uniform distribution; (4.) padding boxes that have the same size as the whole image, which is the default initialization of learnable boxes in [81]. Concatenating Gaussian random boxes works best for DiffusionDet. We use this padding strategy as default.

**Sampling strategy.** We compare different sampling strategies in Table 3c. When evaluating DiffusionDet that does not use DDIM, we directly take the output prediction of the current step as input of the next step. We found that the AP of DiffusionDet degrades with more evaluation steps when neither DDIM nor box renewal is adopted. Besides, only using DDIM or box renewal would bring slight benefits at 4 steps and does not bring further improvements when using more steps. Moreover, our DiffusionDet attains remarkable gains when equipped with both DDIM and renewal. These experiments together verify the necessity of both DDIM and box renewal in the sampling step.

**Box renewal threshold.** As discussed in Section 3.4, the box renewal strategy is proposed to reactivate the predictions whose scores are lower than a specific threshold. Table 3d shows the effect of the score threshold for box renewal. A threshold of 0.0 is no box renewal used. The results demonstrate the threshold of 0.5 performs slightly better than other ones.

**Matching between  $N_{train}$  and  $N_{eval}$ .** As discussed in Sec. 4.2, DiffusionDet has an appealing property of evaluating with an arbitrary number of random boxes. To study how the number of training boxes effects inference performance, we train DiffusionDet with  $N_{train} \in \{100, 300, 500\}$  random boxes separately and then evaluate each of these models with  $N_{eval} \in \{100, 300, 500, 1000\}$ . The results are summarized in Table 3e. First, no matter

how many random boxes DiffusionDet uses for training, the accuracy increases steadily with the  $N_{eval}$  until the saturated point at around 2000 random boxes. Second, DiffusionDet tends to perform better when the  $N_{train}$  and  $N_{eval}$  matches with each other. For example, DiffusionDet trained with  $N_{train} = 100$  boxes behaves better than  $N_{train} = 300$  and 500 when  $N_{eval} = 100$ .

**Accuracy vs. speed.** We test the inference speed of DiffusionDet in Table 3f. The run time is evaluated on a single NVIDIA A100 GPU with a mini-batch size of 1. We experiment with multiple choices of  $N_{train} \in \{100, 300\}$  and keep  $N_{eval}$  same as the corresponding  $N_{train}$ . We see that increasing  $N_{train}$  from 100 to 300 brings 2.5 AP gains while negligible latency cost (31.6 FPS vs. 31.3 FPS). We also test the inference speed of 4 steps when  $N_{train} = 300$ . We observe that more refinements cost brings more inference times and results in less FPS. Increasing the refining step from 1 to 4 provides 0.8 AP gains but makes the detector slower. For reference, we compare DiffusionDet against Sparse R-CNN with 300 proposals, and DiffusionDet with 300 boxes has a very close FPS to Sparse R-CNN.

**Random seed.** Since DiffusionDet is given random boxes as input at the start of inference, one may ask whether there is a large performance variance across different random seeds. We evaluate the stability of DiffusionDet by training five models independently with strictly the same configurations except for random seed. Then, we evaluate each model instance with ten different random seeds to measure the distribution of performance, inspired by [61, 88]. As shown in Figure 5, most evaluation results are distributed closely to 45.0 AP. Besides, the mean values are all above 45.0 AP, and the performance differences among different model instances are marginal, which demonstrates that DiffusionDet is robust to the random boxes and produces reliable results.

## 5. Conclusion and Future Work

In this work, we propose a novel detection paradigm, DiffusionDet, by viewing object detection as a denoising diffusion process from noisy boxes to object boxes. Our noise-to-box pipeline has several appealing properties, including dynamic box and progressive refinement, enabling us to use the same network parameters to obtain the desired speed-accuracy trade-off without re-training the model. Experiments on standard detection benchmarks show that DiffusionDet achieves favorable performance compared to well-established detectors.

To further explore the potential of diffusion model to solve object-level recognition tasks, several future works are beneficial. An attempt is to apply DiffusionDet to video-level tasks, for example, object tracking and action recognition. Another is to extend DiffusionDet from close-world to open-world or open-vocabulary object detection.

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## A. Formulation of Diffusion Model

We provide a detailed review of the formulation of diffusion models, following the notion of [15, 35, 59]. Starting from a data distribution  $\mathbf{z}_0 \sim q(\mathbf{z}_0)$ , we define a forward Markovian noising process  $q$  which produces data samples  $\mathbf{z}_1, \mathbf{z}_2, \dots, \mathbf{z}_T$  by gradually adding Gaussian noise at each timestep  $t$ . In particular, the added noise is scheduled by the variance  $\beta_t \in (0, 1)$ :

$$q(\mathbf{z}_{1:T} | \mathbf{z}_0) := \prod_{t=1}^T q(\mathbf{z}_t | \mathbf{z}_{t-1}) \quad (3)$$

$$q(\mathbf{z}_t | \mathbf{z}_{t-1}) := \mathcal{N}(\mathbf{z}_t; \sqrt{1 - \beta_t} \mathbf{z}_{t-1}, \beta_t \mathbf{I}) \quad (4)$$

As noted by Ho *et al.* [35], we can directly sample data  $\mathbf{z}_t$  at an arbitrary timestep  $t$  without the need of applying  $q$  repeatedly:

$$q(\mathbf{z}_t | \mathbf{z}_0) := \mathcal{N}(\mathbf{z}_t; \sqrt{\bar{\alpha}_t} \mathbf{z}_0, (1 - \bar{\alpha}_t) \mathbf{I}) \quad (5)$$

$$:= \sqrt{\bar{\alpha}_t} \mathbf{z}_0 + \epsilon \sqrt{1 - \bar{\alpha}_t}, \epsilon \in \mathcal{N}(0, \mathbf{I}) \quad (6)$$

where  $\bar{\alpha}_t := \prod_{s=0}^t \alpha_s$  and  $\alpha_t := 1 - \beta_t$ . Then, we could use  $\bar{\alpha}_t$  instead of  $\beta_t$  to define the noise schedule.

Based on Bayes' theorem, it is found that the posterior  $q(\mathbf{z}_{t-1} | \mathbf{z}_t, \mathbf{z}_0)$  is a Gaussian distribution as well:

$$q(\mathbf{z}_{t-1} | \mathbf{z}_t, \mathbf{z}_0) = \mathcal{N}(\mathbf{z}_{t-1}; \tilde{\mu}(\mathbf{z}_t, \mathbf{z}_0), \tilde{\beta}_t \mathbf{I}) \quad (7)$$

where

$$\tilde{\mu}_t(\mathbf{z}_t, \mathbf{z}_0) := \frac{\sqrt{\bar{\alpha}_{t-1}} \beta_t}{1 - \bar{\alpha}_t} \mathbf{z}_0 + \frac{\sqrt{\bar{\alpha}_t} (1 - \bar{\alpha}_{t-1})}{1 - \bar{\alpha}_t} \mathbf{z}_t \quad (8)$$

and

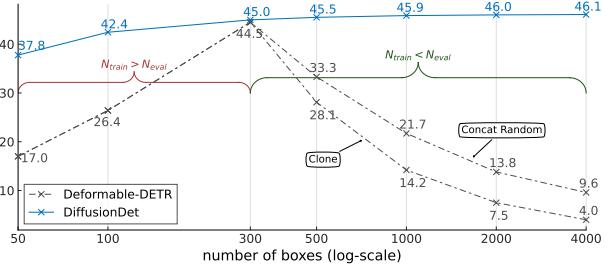
$$\tilde{\beta}_t := \frac{1 - \bar{\alpha}_{t-1}}{1 - \bar{\alpha}_t} \beta_t \quad (9)$$

are mean and variance of this Gaussian distribution.

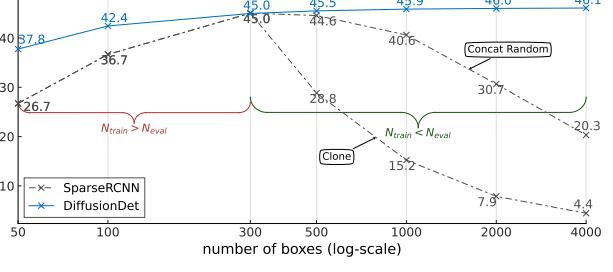
We could get a sample from  $q(\mathbf{z}_0)$  by first sampling from  $q(\mathbf{z}_T)$  and running the reversing steps  $q(\mathbf{z}_{t-1} | \mathbf{z}_t)$  until  $\mathbf{z}_0$ . Besides, the distribution of  $q(\mathbf{z}_T)$  is nearly an isotropic Gaussian distribution with a sufficiently large  $T$  and reasonable schedule of  $\beta_t$  ( $\beta_t \rightarrow 0$ ), which making it trivial to sample  $\mathbf{z}_T \sim \mathcal{N}(0, \mathbf{I})$ . Moreover, since calculating  $q(\mathbf{z}_{t-1} | \mathbf{z}_t)$  exactly should depend on the entire data distribution, we could approximate  $q(\mathbf{z}_{t-1} | \mathbf{z}_t)$  using a neural network, which is optimized to predict a mean  $\mu_\theta$  and a diagonal covariance matrix  $\Sigma_\theta$ :

$$p_\theta(\mathbf{z}_{t-1} | \mathbf{z}_t) := \mathcal{N}(\mathbf{z}_{t-1}; \mu_\theta(\mathbf{z}_t, t), \Sigma_\theta(\mathbf{z}_t, t)) \quad (10)$$

Instead of directly parameterizing  $\mu_\theta(\mathbf{z}_t, t)$ , Ho *et al.* [35] found learning a network  $f_\theta(\mathbf{z}_t, t)$  to predict the  $\epsilon$  or  $\mathbf{z}_0$  from Equation (6) worked best. We choose predicting  $\mathbf{z}_0$  in this work.



(a) Deformable DETR [102] vs. DiffusionDet



(b) Sparse R-CNN [81] vs. DiffusionDet

Figure 6. **Dynamic number of boxes.** All models are trained with 300 candidates (*i.e.*, learnable queries or random boxes). When  $N_{train} > N_{eval}$ , we directly choose  $N_{eval}$  from  $N_{train}$  candidates; when  $N_{train} < N_{eval}$ , we design two strategies, *i.e.*, clone and concat random.

## B. Dynamic Boxes

We further compare the dynamic box property of DiffusionDet with Deformable DETR [102] and Sparse R-CNN [81] in Figure 6. We directly use the provided models in their official code repositories.<sup>1</sup> <sup>2</sup>

We make Deformable DETR to work under  $N_{train} \neq N_{eval}$  setting using the same clone and concat random strategies as DETR as introduced in Section 4.2. For Sparse R-CNN, the strategy concat random is slightly different since Sparse R-CNN has both learnable queries and learnable boxes. Therefore, we concatenate  $N_{eval} - N_{train}$  boxes to existing  $N_{train}$  boxes which are initialized to have the same size as the whole image. Besides, we also concatenate  $N_{eval} - N_{train}$  randomly initialized queries to existing  $N_{train}$  queries in the same way as DETR and Deformable DETR.

Similar to DETR [10], neither Deformable DETR nor Sparse R-CNN has the dynamic box property. Specifically, the performance of Deformable DETR decreases to 9.6 AP when  $N_{eval} = 4000$ , far lower than the peak value 44.5 AP. Although Sparse R-CNN has a slower decrease compared with Deformable DETR, its performance is unsatisfactory when the  $N_{eval}$  is inconsistent with  $N_{train}$ . These findings suggest the distinctive dynamic property of DiffusionDet.

<sup>1</sup><https://github.com/fundamentalvision/Deformable-DETR>

<sup>2</sup><https://github.com/PeizeSun/SparseR-CNN>

## C. Progressive Refinement

method	[E]	step 1	step 3	step 5
DETR	✓	42.03	42.00 (-0.03)	41.88 (-0.15)
			41.35 (-0.68)	41.36 (-0.67)
Deformable DETR	✓	44.46	43.45 (-1.01)	43.40 (-1.06)
			44.03 (-0.43)	44.04 (-0.42)
Sparse R-CNN	✓	45.02	1.32 (-43.70)	0.32 (-44.70)
			42.90 (-2.12)	42.25 (-2.77)
DiffusionDet	✓	44.98	44.93 (-0.05)	44.93 (-0.05)
			45.67 (+0.69)	46.00 (+1.02)

Table 4. **Progressive refinement.** [E] denotes ensembling predictions from multiple steps. NMS is adopted when using ensemble strategy. We show the performance differences of each method with respect to their own performance on step 1 by (-) or (+).

In Table 4 we compare the progressive refinement property of DiffusionDet with some previous approaches like DETR [10], Deformable DETR [102] and Sparse R-CNN [81]. All of these four models have 6 cascading stages as the detection decoder. The refinement refers to the output of the previous 6 stages is taken as the input of the next 6 stages. All model checkpoints are from Model Zoo in their official code repositories.

We experiment with two settings: (1) only use the output of the last reference step as final prediction; (2) use the ensemble of the output of multiple steps as final prediction. For the latter setting, we adopt NMS to remove duplicate predictions among different steps.

We find that all models have performance drop when evaluated with more than one step without ensemble strategy. However, the performance drop of DiffusionDet and DETR is negligible. For example, DiffusionDet with five steps only has 0.05 AP drop. On the contrary, Deformable DETR has more than 1 AP drop, and Sparse R-CNN even totally failed (only gets 1.32 and 0.32 AP with three and five steps, respectively).

Adopting ensemble would mitigate the performance degradation except for DETR. Nevertheless, previous query-based based methods still have performance drop with more steps. In contrast, DiffusionDet turns performance down to up. Specifically, DiffusionDet has performance gains with more refinement steps. For example, DiffusionDet with five steps has 1.02 AP higher than with a single step. Therefore, we use the ensemble strategy as default. To better compare DiffusionDet with DETR, Deformable DETR, and Sparse R-CNN, we also draw the comparison curves of Table 4 in Figure 7.

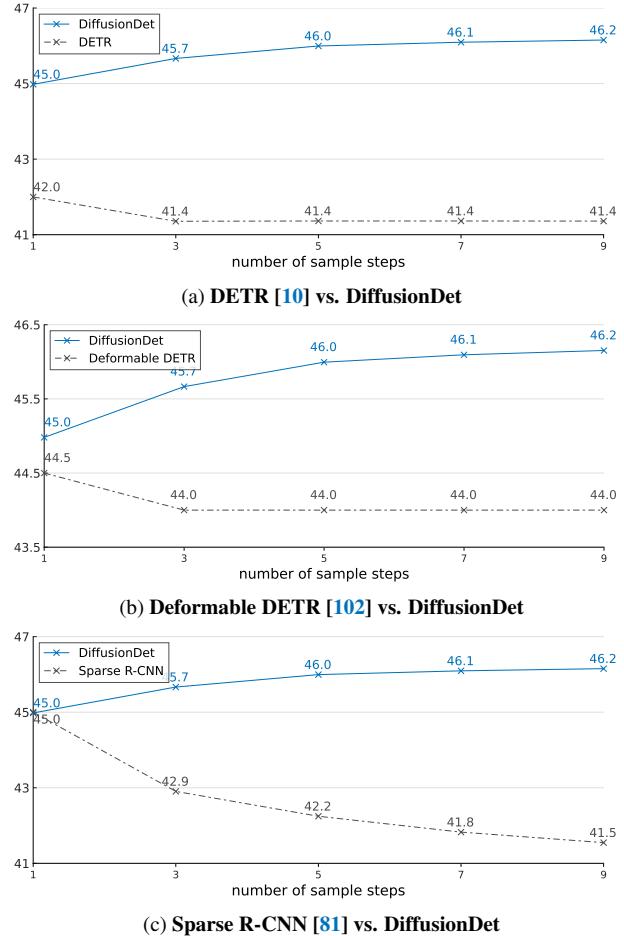


Figure 7. **Progressive refinement.** All models are the provided models in their official code repositories.

## D. Experimental Settings

In this section, we give the detailed experimental settings in Section 4.2 and Section 4.3.

### D.1. DETR with 300 Queries

Since the official GitHub repository<sup>3</sup> of only provides DETR [10] with 100 object queries, we reproduce it with 300 object queries using the official code for fair comparison in Section 4.2. Specifically, we train this model with Detectron2 wrapper based on configuration [https://github.com/facebookresearch/detr/blob/main/d2/configs/detr\\_256\\_6\\_6\\_torchvision.yaml](https://github.com/facebookresearch/detr/blob/main/d2/configs/detr_256_6_6_torchvision.yaml), as summarized in Table 5. We note that configuration only trains the model for about 300 epochs. We only change the NUM\_OBJECT\_QUERIES from 100 to 300 and leave everything else the same as original one.

<sup>3</sup><https://github.com/facebookresearch/detr>

config	value
# object queries	300
optimizer	AdamW [55]
base learning rate	1e-4
weight decay	1e-4
optimizer momentum	$\beta_1, \beta_2=0.9, 0.999$
batch size	64
learning rate schedule	step lr (369600.)
lr decay steps	10
warmup iter	1.0
warmup factor	554400
training iters	full model
clip gradient type	0.01
clip gradient value	2.0
clip gradient norm	RandomFlip, RandomResizedCrop, RandomCrop
data augmentation	

Table 5. DETR reproduction setting.

config	value
optimizer	AdamW [55]
base learning rate	2.5e-5
weight decay	1e-4
optimizer momentum	$\beta_1, \beta_2=0.9, 0.999$
batch size	16
learning rate schedule	step lr (350000, 420000)
lr decay steps	1000
warmup iter	0.01
warmup factor	450000
training iters	full model
clip gradient type	1.0
clip gradient value	2.0
clip gradient norm	RandomFlip, RandomResizedCrop, RandomCrop
data augmentation	

Table 6. COCO setting.

config	value
optimizer	AdamW [55]
base learning rate	2.5e-5
weight decay	1e-4
optimizer momentum	$\beta_1, \beta_2=0.9, 0.999$
batch size	16
learning rate schedule	step lr (210000, 250000)
lr decay steps	1000
warmup iter	0.01
warmup factor	270000
training iters	full model
clip gradient type	1.0
clip gradient value	2.0
clip gradient norm	RandomFlip, RandomResizedCrop, RandomCrop
data augmentation	RepeatFactorTrainingSampler
data sampler	0.001
repeat thres.	

Table 7. LVIS setting.

## D.2. Benchmark on COCO and LVIS

In Section 4.3, we benchmark DiffusionDet on COCO dataset and LVIS dataset. The training configuration is in Table 6 and Table 7, respectively.

## E. Training Loss

We adopt set prediction loss [10, 81, 102] on the set of  $N_{train}$  predictions for DiffusionDet. Set prediction loss requires pairwise matching cost between predictions and ground truth objects, taking into account both the category and box predictions. The matching cost is formulated as :

$$\mathcal{C} = \lambda_{cls} \cdot \mathcal{C}_{cls} + \lambda_{L1} \cdot \mathcal{C}_{L1} + \lambda_{giou} \cdot \mathcal{C}_{giou}, \quad (11)$$

where  $\mathcal{C}_{cls}$  the focal loss [50] between prediction and ground truth class labels. Besides, our boxes loss contains  $\mathcal{C}_{L1}$  and  $\mathcal{C}_{giou}$ , which are most commonly-used  $\ell_1$  loss and generalized IoU (GIoU) loss [67].  $\lambda_{cls}$ ,  $\lambda_{L1}$  and  $\lambda_{giou} \in \mathbb{R}$  are weight of each component to balance to overall multiple losses. Following [10, 81, 102], we adopt  $\lambda_{cls} = 2.0$ ,  $\lambda_{L1} = 5.0$  and  $\lambda_{giou} = 2.0$ .

We assign multiple predictions to each ground truth with the optimal transport approach [22, 23]. Specifically, for each ground-truth, we select the top-k predictions with the least matching cost as its positive samples, others as negatives. Then, DiffusionDet is optimized with a multi-task loss function:

$$\mathcal{L} = \lambda_{cls} \cdot \mathcal{L}_{cls} + \lambda_{L1} \cdot \mathcal{L}_{L1} + \lambda_{giou} \cdot \mathcal{L}_{giou}, \quad (12)$$

The component of training loss is the same as the matching cost, except that the loss is only performed on the matched pairs.

## F. Visualization

We visualize our sampling step of DiffusionDet in Figure 8. The model is running with 300 boxes. For better visualization, we only draw 50 boxes in the image.

(a) Initial random boxes are input into the detection detector. The random boxes are sampled from the Gaussian distribution.

(b) The detection decoder predicts the category scores and box coordinates of the current step. In sub-figure (b), the color brightness is proportional to the score value, where the deep red is high score, and white is low score.

(c) DDIM estimates the boxes for the next step.

(d) Those boxes with lower scores than the threshold are dropped.

(e) New random boxes sampled from a Gaussian distribution are concatenated to the remaining boxes. This new set of boxes are input to the detection detector.

(f) After multiple steps of refinement, final predictions are obtained.

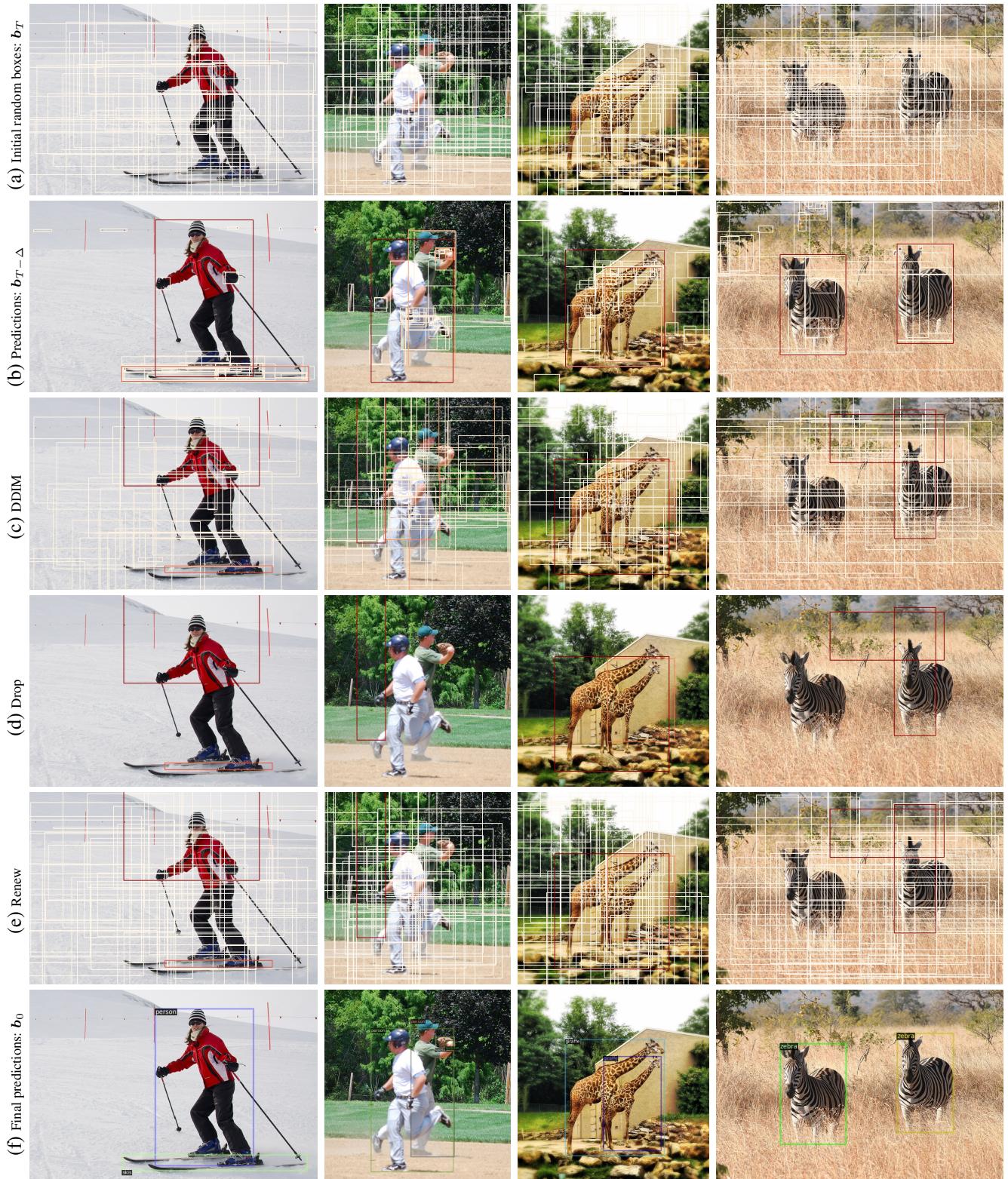


Figure 8. **Visualization** of sampling step in inference.