

# Multi-Task Incremental Learning for Object Detection

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**Abstract.** Training an object detector incrementally has hardly been explored. In this paper, we propose attentive feature distillation which leverages both bottom-up and top-down attentions to mitigate forgetting in incremental detection. Then, we systematically analyze the proposed distillation method in different scenarios across various domains and categories. We find out that, contrary to common understanding, domain gaps have relatively smaller negative impact on incremental detection, while category differences are the major problem. For the difficult cases, where the domain gaps and especially categories differences are large, we propose an adaptive exemplar sampling method to select diverse and informative samples from entire datasets, to further prevent forgetting. Experimental results show that we achieve the state-of-the-art performance in three different scenarios across seven object detection benchmark datasets.

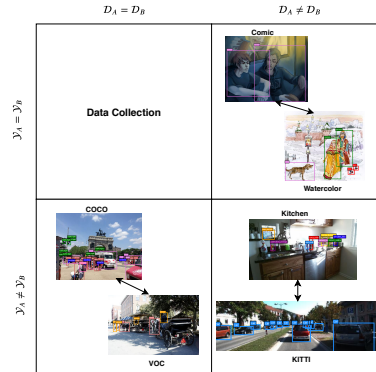
## 1 Introduction

Object detection has improved significantly in recent years [3,12,22,35] on multiple challenging benchmarks, such as PASCAL VOC [9] and MS COCO [23]. However, most of these existing detectors are still domain and category specific. To extend the capability of the detector to new domains and/or categories, retraining with data from current and previous domains is usually necessary. Unfortunately, in real-world scenarios, legacy data from previous domains can be lost, proprietary, or simply too expensive to use in new domains [21]. For example, for models deployed on edge devices, it is unlikely that they can still access the original training data. Even if they do have access, the limited resources on edge devices make it difficult to retrain with full training data. If we want to learn to detect/localize new concepts from new domains on devices for these models *without losing the detection ability in previous domains*, we need to develop a new learning scheme.

In this paper, we aim to develop such an object detector that can learn across multiple domains incrementally. We approach this problem by first studying the methods applying distillation to incremental learning for classification to avoid *catastrophic forgetting* [7,21]. However, naively transferring these distillation methods to object detection introduces new problems. In state-of-the-art two-stage and some one-stage detectors [34,35], many, even the majority of box hypotheses (“proposals”) provided by either regional proposal networks or dense sampling, are background. If we equally distill from all hypotheses without considering their importance to the tasks, we could end

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**Fig. 1.** Given  $A, B$  two object detection tasks,  $\mathcal{D}_A, \mathcal{D}_B$  their corresponding domains, and  $\mathcal{Y}_A, \mathcal{Y}_B$  their corresponding categories, there are four different scenarios when learning  $A$  and  $B$  sequentially: more training data (top-left), same categories but different domains (top-right), different categories but same domains (bottom-left), and different categories and domains (bottom-right).

up with more noise than useful information. Moreover, it has been shown that context information is also important in object detection [41]. Hence, for incremental detection, we need to balance the distillation in foreground objects, contexts and possible useful background information. With this principle in mind, we develop an attentive feature distillation method, which leverages both bottom-up and top-down attention maps to achieve effective distillation in detection.

Then, we study the effects of domain and category differences on catastrophic forgetting by applying our proposed method to various scenarios. For instance, VOC and COCO are from similar domains, but COCO has 60 more categories, how would forgetting happen if we train from VOC to COCO or from COCO to VOC? Watercolor and Comic [18] share the same categories, but they are from different domains, how would the domain shift affect the continual learning process? KITTI [10] and Kitchen [11] have disjoint categories and significant domain discrepancies; can we learn those sequentially without forgetting? To answer these questions and better understand forgetting across domains, we conducted a comprehensive analysis of different scenarios, as shown in Figure 1.

We find that categories differences cause a bigger problem, and just using attention is not enough to prevent forgetting in these difficult cases. Therefore, we propose to use of a small number of exemplars from previous tasks to further mitigate forgetting. Specifically, we rank the samples by the number of ground truth bounding boxes, then sample them adaptively with a fixed budget to balance between the number of bounding boxes and the diversity of exemplars.

To summarize, we make the following contributions:

- We propose an attentive feature distillation approach to mitigate forgetting for incremental object detection.
- We analyze the effects of domain gaps and category differences on catastrophic forgetting for incremental object detection.

- We propose an adaptive exemplar sampling to choose samples with more information and diversity for difficult cases.

Experimental results across seven datasets demonstrate the effectiveness of our proposed method and show interesting behaviors in different scenarios.

## 2 Related Work

**Object Detection** Object detection networks can be divided into two categories: two-stage or one-stage. Faster-RCNN [35] is a representative two-stage method with a region proposal network (RPN) and a classification and regression network (Fast-RCNN [12]). YOLO [33] and SSD [24] are representatives of one-stage methods, which predict bounding boxes and class probabilities directly from full images in one step. We show experimental results with Faster-RCNN, although our method applies to other two-stage and one-stage methods. Large datasets have been a driven force in object detection, such as PASCAL VOC [9], MSCOCO [23]. However, most of the existing detectors are domain and category specific.

**Incremental Learning** Most works on incremental learning focus on classification problems, which can be roughly divided into three main families [6,30]. The first family is regularization-based, which contain both data-focused and prior-focused approaches. The first subset is composed of distillation approaches such as LwF [21] using probability distillation and LwM [7] using attention distillation. The second subset estimates the importance of network parameters, and it applies a higher penalty on those that show a significant change when switching from one task to another [2,19,21,25,46]. The next family prevents catastrophic forgetting by growing a sub-network or learning a mask for each task [20,27,28,37,38]. Finally, rehearsal-based approaches form the last family, which either store a small number of training samples from previous tasks [4,26,32], or use a generative model to sample synthetic data from previously learned distributions [39,43]. There are few works on incremental object detection learning. Shmelkov et al. [40] proposed the first work to learn an object detector incrementally by adding one or a few classes at a time within one single domain.

**Knowledge Distillation** Probability distillation was proposed by Hinton et al. [15] to compress networks for fast inference. It trains a smaller student network from the softened output of a wider teacher network. Romero et al. [36] extended this idea to learn intermediate features (Feature distillation) from teacher networks using a two-stage strategy. Further, Zagoruyko et al. [45] proposed to mimic the attention maps from teacher networks (Attention distillation), computed by activations or gradients. Due to the simple implementation and success of knowledge distillation, the idea has been applied to incremental learning [1,7,21,32]. However, naively transferring these distillation methods to object detection introduces new problems since many region proposals in detection are background.

**Transfer Learning** Convolutional Neural Networks (CNNs) models trained on ImageNet have been widely used for transfer learning. It can be done either using a pre-trained model as a feature extractor[8] or fine-tuning the model on the target data[29,13].

After transfer learning, normally only performance on target task is evaluated regardless how it performs on the original task. In this paper, we do transfer object detector learning across domains incrementally but aim at avoiding the catastrophic forgetting of previous domains. Since there is no prior work on analyzing the relation between the forgetting and domain-category differences, we conduct in-depth forgetting analysis during transfer learning.

### 3 Preliminaries

In this section, we introduce the notation for object detection in incremental learning and present the proposed approach in Sec. 4.

#### 3.1 Object Detection

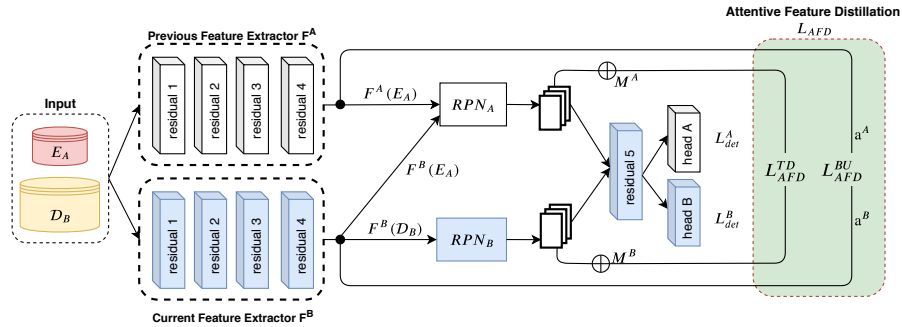
An object detector is a function that maps an image  $\mathbf{x} \in \mathcal{X}$  to an output  $\mathbf{y} \in \mathcal{Y}$  of multiple bounding box and label pairs, where each bounding box is the location of the corresponding object label. Object detectors are typically trained from a dataset  $\{(\mathbf{x}_i, \mathbf{y}_i)\}_{i=1}^N$  of size  $N$ , by minimizing a loss or objective  $L$ . In the case of a typical two-stage detector, the function is composed of three elements, a *feature extractor*  $F$  that maps a (region of the) image onto a vector or probability space,  $\mathbf{z} = F(\mathbf{x})$ , a *region proposal network* (RPN),  $R$  that samples hypotheses  $\hat{\mathbf{y}} = R(\mathbf{z})$ , and a classifier, or *head*  $H$  that measures the fit of the hypothesis,  $H(\hat{\mathbf{y}}, \mathbf{y})$ .

$$L(F, R, H) = -\frac{1}{N} \sum_{i=1}^N L_{\text{det}}(H(R(F(\mathbf{x}_i))), \mathbf{y}_i), \quad L_{\text{det}} = L_{\text{reg}} + L_{\text{cls}}, \quad (1)$$

where detection loss  $L_{\text{det}}$  quantifies both classification error for the label and regression error for the bounding box(es),  $L_{\text{cls}}$  and  $L_{\text{reg}}$  are defined as cross entropy loss and Smooth-L1 loss, respectively. The functions  $F, R, H$  are typically implemented using deep neural networks (DNNs), and training or learning corresponds to minimizing the loss with respect to their parameters, or *weights*.

#### 3.2 Incremental Object Detection

In continual/incremental learning,  $T$  tasks are presented sequentially, each corresponding to a different dataset of *domains*  $\mathcal{D}_1, \dots, \mathcal{D}_T$  and categories  $\mathcal{Y}_1, \dots, \mathcal{Y}_T$ . Since training  $T$  models independently is inefficient both statistically and computationally, in typical incremental/continual learning setting, parts of the model are shared across all tasks, most notably the feature extractor  $F$ . Then, incremental learning methods focus on solving the catastrophic forgetting problem when training the tasks sequentially with shared backbone features [19]. Due to the complexity of background and diversity in sizes and numbers of foreground objects, compared to incremental classification, incremental detection needs more specialized design to mitigate forgetting, which we will introduce in Section 4. Without losing of generality, we present and analyze our approach on the case of two-task incremental detection, as extensions to more tasks is straightforward. Experiments on three and more tasks can be found in Section 5.2.



**Fig. 2.** The proposed framework for learning tasks  $A, B$  sequentially based on Faster-RCNN (Best view in color). White modules on top are frozen after learning task  $A$ . When learning task  $B$ , we first duplicate the blue modules (including the RPN) and add a new head. Then, we combine data from task  $B$  ( $\mathcal{D}_B$ ) and exemplars from task  $A$  ( $E_A$ ). In green, our proposed approach combines bottom-up attention ( $L_{AFD}^{BU}$ ) from the outputs of the feature extractors with top-down attention ( $L_{AFD}^{TD}$ ) from the output bounding boxes of the RPN. The attentive feature distillation loss ( $L_{AFD}$ ) is then combined with the usual object detection losses ( $L_{det}^A, L_{det}^B$ ). The same procedure can be easily extended to more tasks.

## 4 Proposed Approach and Analysis

In this section, we decompose two-task incremental learning into four different scenarios for in-depth understanding of how domain gaps and category differences contribute to catastrophic forgetting. Then we describe our overall framework on incremental detection with general two-stage detectors and the two technical contributions of this paper: attentive feature distillation that uses both bottom-up and top-down attention, and adaptive exemplar sampling to balance the number of bounding boxes and maintain diversity of exemplars.

### 4.1 Four Different Scenarios for Two-Task Incremental Detection

We consider four different scenarios in two-task incremental detection, using the two tasks  $A$  and  $B$  for reference (Fig. 1): (i) both domains and classes are the same, so there is no covariate shift; (ii) Same domain, different categories,  $\mathcal{D}_A = \mathcal{D}_B$  and  $\mathcal{Y}_A \neq \mathcal{Y}_B$ , corresponding to intra-domain sequential learning. (iii) Domain shift,  $\mathcal{D}_A \neq \mathcal{D}_B$  but  $\mathcal{Y}_A = \mathcal{Y}_B$ , corresponding to domain adaptation, say from real to synthetic images. Finally (iv) both domains and categories differ,  $\mathcal{D}_A \neq \mathcal{D}_B$  and  $\mathcal{Y}_A \neq \mathcal{Y}_B$ . For example, KITTI and Kitchen datasets have different domain (indoor vs. outdoor imagery) and categories. In the following sections, we focus on the last three non-trivial scenarios.

### 4.2 Framework

Our incremental detection system is based on general two-stage object detection algorithms (Faster-RCNN [35], FPN [22]) in favor of its performance benefit compared

to one-stage detectors (YOLO [33], SSD [24]). We assume ResNet-style networks (ResNet [14], SE-ResNet [16]) as backbone. For incremental learning, we employ separate RPN and detection head for each task and share most of the backbone network.

Specifically, for the two-task case, as shown in Figure 2, we train the first task  $A$  using Faster-RCNN with data  $\mathcal{D}_A$ . Then we train on task  $B$  with data  $\mathcal{D}_B$  using our proposed attentive feature distillation (Section 4.3) and adaptive exemplar sampling method (Section 4.5). After learning on the current task, only current model is needed to do inference for all tasks and previous model is removed from the memory. This framework could be easily extend to more tasks.

By fusing the usual object detection losses with the proposed attention feature distillation loss, the final objective function for incremental object detection learning from task A to task B is defined as:

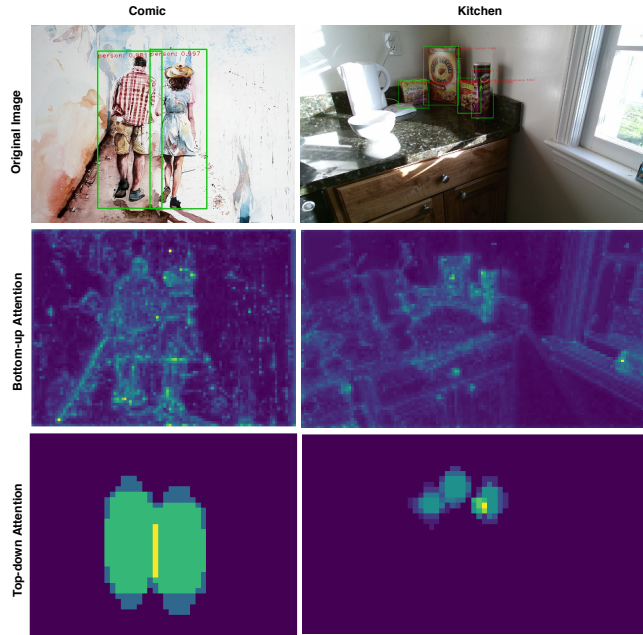
$$L(F^B, R^B, H^B) = L_{det}^B + L_{det}^A + \lambda L_{AFD}, \quad (2)$$

where  $\lambda$  is the trade-off parameter to balance the current learning objective and distillation objective to avoid forgetting, and  $L_{det}$  is the standard Faster-RCNN detection loss.  $L_{det}^B$  is updated using data from current task B and  $L_{det}^A$  is learned with a few exemplars (in Section 4.5) selected from previous task A. We will explain  $L_{AFD}$  in the next section.

### 4.3 Attentive Feature Distillation (AFD)

To mitigate forgetting in object detection, naively applying feature or probability distillation widely used in classification is ineffectively due to several reasons: 1) For feature distillation, due to complexity of background and various sizes/numbers of foreground objects, treating the whole feature map equally will lead to relatively weak guidance from the important foreground objects. 2) Similarly, for probability distillation, as there are large amounts of background regional proposals, treating both background and foreground proposals equally will result in ineffective distillation and alignments on foreground proposals. Therefore, we need to have top-down(TD) attention from the ground-truth bounding boxes to guide the distillation process. On the other hand, it has been shown in the literature that context information is very important in object detection [5]. Thus, we cannot simply discard all background information. It would be beneficial to preserve the useful background information and contexts around foreground objects. Since there are no annotations for context and background, we propose to use bottom-up (BU) attention as well as a smart sampling technique for top-down attention to harvest this information. Without losing of generality, we apply both top-down attention and bottom-up attention in feature distillation as it has shown better results in our experiments, but the same principle can also be used for probability distillation. Therefore, we will refer to our proposed attention as attentive feature distillation (AFD).

Assume we learn from task  $A$  to task  $B$ , the bottom-up AFD is defined as integrating self-attention maps and feature maps. Here self-attention maps are summation of all channels of the feature maps. They capture the important blobs in the feature maps based on network itself. By combining self-attention maps and feature maps, we can capture the important context and background information smoothly and naturally during training, as shown in the middle row in Figure 3.



**Fig. 3.** Examples of attention maps. Original images (*top*), bottom-up attention (*middle*), top-down attention (*bottom*) from Comic (*left*) and Kitchen (*right*) object detection datasets.

Formally, we define bottom-up AFD as:

$$L_{\text{AFD}}^{\text{BU}}(F^B) = \frac{1}{2} \left\| \frac{\mathbf{a}_i^B}{\|\mathbf{a}_i^B\|} F^B(\mathbf{x}_i) - \frac{\mathbf{a}_i^A}{\|\mathbf{a}_i^A\|} F^A(\mathbf{x}_i) \right\|^2. \quad (3)$$

Here  $F^B$  and  $F^A$  are the feature extractors of current task  $B$  and previous task  $A$  (Fig. 2) and the self-attention maps are

$$\mathbf{a}_i = \sum_{j=1}^c |F(\mathbf{x}_i)^j|^2, \quad (4)$$

where  $c$  is the number of channels per activation.

On the other hand, top-down attention was introduced by [41] to transfer knowledge from deep models to shallow ones. For each ground truth bounding box, intersection-over-union (IoU) is computed for all box hypotheses (“proposals”) provided by the RPN. A threshold is set for  $\frac{1}{2} \max(\text{IoU})$ . To further capture the context around ground-truth bounding boxes, we propose two modifications:

- For each bounding box, we compute the mean of all overlapping proposals that exceed the IoU threshold, which yields their centroids. Then, we obtain the top-down attention  $M$  by looping over all ground-truth boxes and then we do  $L_2$  normalization (as shown in Figure 3). In this way, we not only capture the ground-truth boxes, but also some contextual information around them.

**Table 1.** Analysis of performance (mAP) and forgetting on different scenarios. Arrows indicate order of learning. We evaluate on both datasets after training on the second dataset incrementally.

Methods	$\mathcal{D}_A \neq \mathcal{D}_B$ and $\mathcal{Y}_A \neq \mathcal{Y}_B$				$\mathcal{D}_A \neq \mathcal{D}_B$ and $\mathcal{Y}_A = \mathcal{Y}_B$				$\mathcal{D}_A = \mathcal{D}_B$ and $\mathcal{Y}_A \neq \mathcal{Y}_B$			
	KITTI → Kitchen	Kitchen → KITTI	KITTI → Kitchen	Kitchen → KITTI	Comic → Watercolor	Watercolor → Comic	Watercolor → Comic	Comic → Watercolor	VOC → COCO	COCO → VOC	VOC → COCO	COCO → VOC
Joint Training	53.7	70.9	70.9	53.7	45.1	50.0	50.0	45.1	74.1	47.8	47.8	74.1
Fine-tuning	10.9 (-42.8)	68.2	9.2 (-61.7)	54.0	39.6 (-5.5)	48.8	46.4 (-3.6)	43.4	74.9 (+0.8)	48.4	20.1 (-27.7)	75.9
AFD (bottom-up)	25.2 (-28.5)	68.8	13.1 (-57.8)	50.9	43.1 (-2.0)	48.3	47.5 (-2.5)	43.5	75.4 (+1.3)	45.1	23.1 (-24.7)	76.2
AFD (top-down)	33.9 (-19.8)	72.1	16.8 (-54.1)	51.2	43.6 (-1.5)	45.9	51.3 (+1.3)	46.2	76.0 (+1.9)	45.5	28.1 (-19.7)	76.8
AFD (both)	36.6 (-17.1)	72.0	20.5 (-50.4)	50.5	42.9 (-2.2)	48.5	49.4 (-0.6)	45.5	75.4 (+1.3)	45.1	27.8 (-20.0)	77.1

- We do the same normalization as in Eq. 3, using the top-down attention maps  $M$  instead of the self-attention maps.

Therefore, the top-down AFD objective is defined as:

$$L_{\text{AFD}}^{\text{TD}}(F^B) = \frac{1}{2} \left\| \frac{M_i^B}{\|M_i^B\|} F^B(\mathbf{x}_i) - \frac{M_i^A}{\|M_i^A\|} F^A(\mathbf{x}_i) \right\|^2 \quad (5)$$

Top-down AFD focuses on distillation on foreground objects, which is crucial for object detection algorithms.

To leverage both rich context information and foreground objects, The final AFD loss function is defined as:

$$L_{\text{AFD}}(F^B) = L_{\text{AFD}}^{\text{BU}} + L_{\text{AFD}}^{\text{TD}}. \quad (6)$$

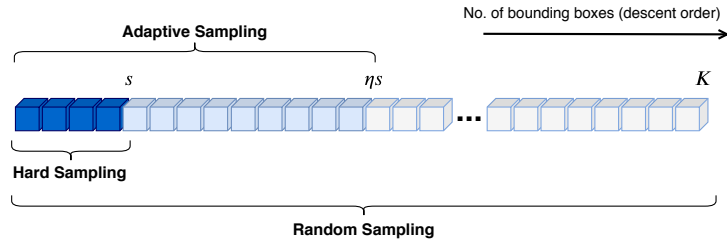
Experiments in Table 1 demonstrate the benefits of combining both attention maps, especially in difficult cases, e.g., KITTI and Kichen.

#### 4.4 Analysis of the Proposed AFD on Three Different Scenarios

In this section, we analyze the effect of forgetting on different scenarios with the proposed AFD to understand which factor impact forgetting the most in incremental detection, and how can we improve on the difficult cases. Implementation and dataset details can be found in Section 5.

As discussed in Section 4.1, we decompose two-task incremental learning into 4 scenarios with different domains and categories differences. We focus on the three non-trivial scenarios, as show in Table 1: 1) KITTI and Kitchen ( $\mathcal{D}_A \neq \mathcal{D}_B$ ,  $\mathcal{Y}_A \neq \mathcal{Y}_B$ ); 2) Watercolor and Comic ( $\mathcal{D}_A \neq \mathcal{D}_B$ ,  $\mathcal{Y}_A = \mathcal{Y}_B$ ); 3) VOC and COCO ( $\mathcal{D}_A = \mathcal{D}_B$ ,  $\mathcal{Y}_A \neq \mathcal{Y}_B$ ).

One interesting observation we can see from the results is that domain gaps actually have less impact in forgetting. Specifically, in Watercolor and Comic, forgetting is less severe compared to other two scenarios by a large margin, even for just Fine-tuning. By using our proposed AFD, we can achieve similar performance as Joint Training. The drops are just 2.2 and 0.6 for each direction, respectively. One possible explanation for this phenomenon is that, although there exists domain discrepancy between Watercolor and Comic, since the categories and general perspective of the objects remain the same, the backbone features are quite similar between the two tasks. Training the RPN and detection head for the new task also would not disturb the backbone features much due to same categories. This can be seen from the low forgetting for vanilla Fine-tuning.



**Fig. 4.** Illustration of different sampling methods. By adapting the value of  $\eta$ , we can switch among random sampling, hard sampling and adaptive sampling.

The other observation is that if we continually train on a new task in the same domain, with all the classes from the previous task, i.e., VOC to COCO, there is no forgetting at all. Actually, performances improve for all methods. On the other hand, there is severe forgetting of up to 20% mAP when continually train on a new task with less classes from the previous task, i.e., COCO to VOC. In this case, neither Fine-tuning nor AFD can avoid the forgetting, though AFD still manages to improve over Fine-tuning from 20.1  $\rightarrow$  27.8. Therefore, learning the RPN and detection head on tasks with more classes actually enhance the backbone features for the previous task, while learning on tasks with less classes can cause severe forgetting. In the latter case, the same feature maps that produce positive signal in the previous RPN and detection head could be negative in new heads. Thus the gradients propagated back to the backbone are significantly different, causing severe forgetting.

Unsurprisingly, for Kitchen and KITTI, where there are the vast differences in categories and domains, we observe severe forgetting. Fine-tuning forgets the first task almost completely while our proposed AFD can reduce the performance drops from 53.7  $\rightarrow$  36.6 and 70.9  $\rightarrow$  20.5, respectively. However, with just attention, it is hard to mitigate the forgetting effect even with the best distillation methods for this scenario.

To solve the forgetting problem in the difficult cases for the last two scenarios, we propose to explore usage of exemplar in the following section.

#### 4.5 Adaptive Exemplar Sampling

In incremental learning, it is common to store a small number of samples (“exemplars”) to avoid catastrophic forgetting [4,32] while still maintaining training efficiency. Thus, we consider similar strategy for the difficult cases.

Random sampling is effective for classification problems [4], so we use it as a baseline in object detection. Since the number of bounding boxes can vary in each sample image, we propose *hard sampling* as another baseline, which consists of keeping images with the most bounding boxes as exemplars. However, for video data (e.g., KITTI or Kitchen), the diversity of samples can be reduce by using hard sampling, as the images with more bounding boxes are more likely to be sampled from consecutive frames.

To avoid this drawback, we propose *adaptive sampling*: For each category, we rank all  $K$  samples in decreasing order by number of bounding boxes. Given a budget of  $s$  exemplars with  $K \gg s$  and  $\eta \in \mathbb{N}$ , we randomly sample  $s$  exemplars from the ordered

list  $(1, \eta s)$ . We define three different sampling cases: when  $\eta = 1$ , we select the samples with the most bounding boxes (hard sampling), when  $\eta \geq \frac{K}{s}$  we sample among all images randomly (random sampling), and when  $1 < \eta$  and  $\eta < \frac{K}{s}$ , it balances the number of bounding boxes and diversity of exemplars through the choice of  $\eta$ . An illustration of different sampling methods is shown in Figure 4.

## 5 Experiments

We use a Pytorch [31] implementation of Faster-RCNN [44] with SE-ResNet-50 [17] pre-trained on ImageNet. As usual in detection, the first convolution layer, the first residual block, and all BN layers are fixed during training. We consider different combinations of the following datasets: Watercolor [18], Clipart [18], Comic [18], Kitchen [11], KITTI [10], VOC [9], COCO [23]. All train and test splits are the same as in [42]. The Pascal VOC mean average precision (mAP) is used for evaluation of all cases.

**Training details:** Following [44], we use the default parameters for Faster-RCNN with 4 anchor scales and 3 anchor ratios. Learning rate is set to 0.01 for 10 epochs and 0.001 for the last 2. For small datasets (Watercolor, Clipart, Comic) we use a batch size of 8 on 4 synchronized GPUs. For the other datasets, we use a batch size of 16. For all experiments, we set  $\lambda = 10^{-4}$  from Eq. 2.

**Compared methods:** We compare AFD with LwF Detection [40], Feature Distillation, Attention Distillation, and two other baselines (Joint Training and Fine-tuning). For LwF Detection, we follow [40] to embed the loss function into our framework. For Joint Training, we train a universal detector using all training data at the same time, which can be seen as *upper bound* for incremental learning. Fine-tuning is done by training all object detection tasks sequentially without any additional loss.

**Table 2.** Results on KITTI and Kitchen (100 exemplars). The Pascal VOC mean average precision (mAP) is evaluated on both datasets after training on the second dataset. Arrows indicate order of learning. "Average" means the average of numbers in the same row for easy comparison.

Methods	Kitchen $\rightarrow$ KITTI	KITTI $\rightarrow$ Kitchen	Average
Joint Training	74.0	54.3	64.1
Fine-tuning w/o exemplars	9.2	54.0	35.6
Fine-tuning w/ exemplars	63.0	54.5	56.6
LwF Detection	59.9	54.7	56.0
Feature Distillation	62.7	54.4	55.4
Attention Distillation	64.2	52.8	57.0
AFD (Ours)	68.6	53.4	<b>60.6</b>

### 5.1 Comparisons on Two-Task Setting

In this section, we compare our proposed methods to other baseline methods in three different scenarios for two-task setting.

**Table 3.** Results on Comic and Watercolor (without exemplars). Arrows indicate order of learning.

Methods	Comic $\rightarrow$ Watercolor		Watercolor $\rightarrow$ Comic		Average
Joint Training	45.3	49.7	49.7	45.3	47.5
Fine-tuning	39.6	48.8	46.4	43.4	44.6
LwF Detection	39.8	48.3	44.2	44.7	44.3
Feature Distillation	39.7	48.5	43.8	41.0	43.3
Attention Distillation	40.9	47.9	48.1	44.6	45.4
AFD (Ours)	42.9	48.5	49.4	45.5	<b>46.6</b>

**Table 4.** Results from COCO to VOC (500 exemplars). Arrows indicate order of learning.

Methods	COCO $\rightarrow$ VOC		Average
Joint Training	44.3	79.0	61.7
Fine-tuning w/o exemplars	20.1	75.9	48.0
Fine-tuning w/ exemplars	28.7	73.3	51.0
LwF Detection	26.6	73.0	49.8
Feature Distillation	26.9	72.4	49.7
Attention Distillation	28.5	73.0	50.8
AFD (Ours)	36.8	75.2	<b>56.0</b>

**KITTI and Kitchen.** As shown in Table 2, Fine-tuning usually suffers from catastrophic forgetting without exemplars, however with 100 exemplars we can see that it performs quite well and obtains similar accuracy as LwF Detection [40]. Feature Distillation is worse in both cases, while Attention Distillation performs better by filtering out the noisy information. Our proposed AFD outperforms all other methods and baselines and is close to joint training with only 100 exemplars (less than 2% of KITTI data and less than 3% of Kitchen data).

**Comic and Watercolor.** In the scenario of domain shift when we have the same categories but different domains, we compare with the methods and baselines without using exemplars due to much less forgetting, as demonstrated in Table 1. As seen in Table 3, our AFD achieves 46.6 mAP compared to Joint Training with 47.5 in average. It shows that we can avoid forgetting in this scenario even without using any data from previous tasks, which is much efficient than Joint training.

**COCO to VOC.** We present results on this relatively larger datasets in Table 4. Since there is no forgetting from VOC to COCO (seen in Table 1), we only report results from COCO to VOC. COCO is a more challenging dataset compared to others because of the large amount of data and categories. Our AFD surpasses the Attention Distillation methods by 5.2. However, there is still space for improvement until achieving similar performance as joint training. We also show some qualitative results on COCO before and after training on VOC (see Figure 5). We can clearly see that fine-tuning with exemplars outputs less bounding boxes or has lower prediction confidence on COCO



**Fig. 5.** Examples of predictions on COCO after training on VOC for Fine-tuning (top), Joint Training (bottom) and Ours (middle). Finetuning tends to forget objects, such as the hydrant, the tie or the keyboard. Ours is capable of detecting all those objects and only misses the ball and the bicycle. Joint Training is capable of detecting all the objects missed by the other methods, but is not capable of differentiating between the two elephants. In the last column, Ours predicts the objects with higher confidence than the other methods.

after learning on VOC. Our proposed AFD closes the gap between fine-tuning and joint training by forgetting less and predicting more confident scores.

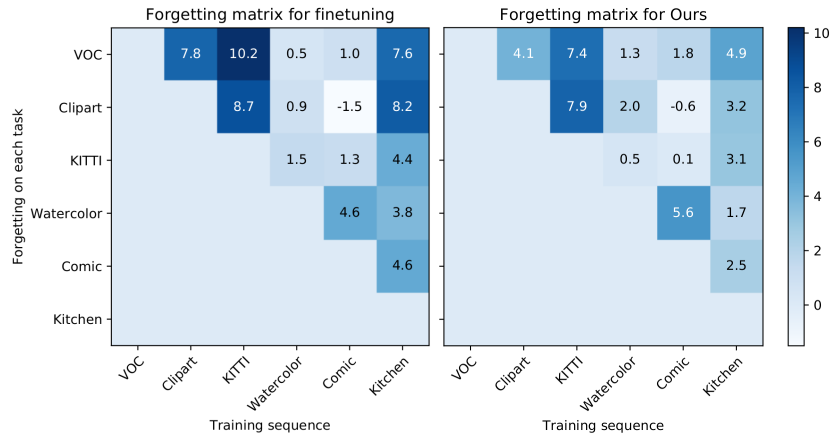
## 5.2 Comparisons on More Tasks

**Table 5.** Results on KITTI, VOC and Kitchen (300 exemplars). Arrows indicate order of learning. The Pascal mAP is reported on all datasets after learning on the last.

	KITTI $\rightarrow$ VOC $\rightarrow$ Kitchen			Kitchen $\rightarrow$ VOC $\rightarrow$ KITTI		
Fine-tuning w/ exemplars	43.8	55.0	68.8	64.6	58.4	57.5
AFD (Ours)	53.2	63.4	71.2	69.1	65.0	59.6

In this section, we show results in more realistic and challenging settings learning incrementally with three and six tasks. In Table 5, we perform a sequence of incremental training on KITTI, VOC, and Kitchen. The performances are evaluated after training the last dataset. Our proposed approach clearly outperforms Fine-tuning with exemplars, which is a competitive baseline, as seen in previous experiments, in both directions of the sequential training.

To further scale-up our incremental object detector, we conduct experiments on a sequence of six different datasets: VOC, Clipart, KITTI, Watercolor, Comic, and Kitchen.



**Fig. 6.** Forgetting matrix for Fine-tuning w/ exemplars (left) and AFD (right) on sequential learning of six tasks. Horizontal axis represents the sequential learning order of different tasks. Vertical axis is forgetting mAP for each task after learning on the task in the horizontal axis. Each Row represents total forgetting progression of each dataset over the learning sequence by adding all values. The lighter the color, the less the forgetting.

To illustrate the dynamic process of forgetting after training on each dataset, we show in Figure 6 a forgetting matrix. Horizontal axis represents the learning order of different tasks. Vertical axis is forgetting measured in mAP for each task after learning the next task. It reflects the forgetting of current or previous datasets after training each task. The total forgetting for each datasets can be obtained by adding all values on that row. For instance, after training the last task, performance on VOC Fine-tuning with exemplars drops 27.1, while only 19.5 for Ours. Overall, our method demonstrate clear advantage to Fine-tuning baseline.

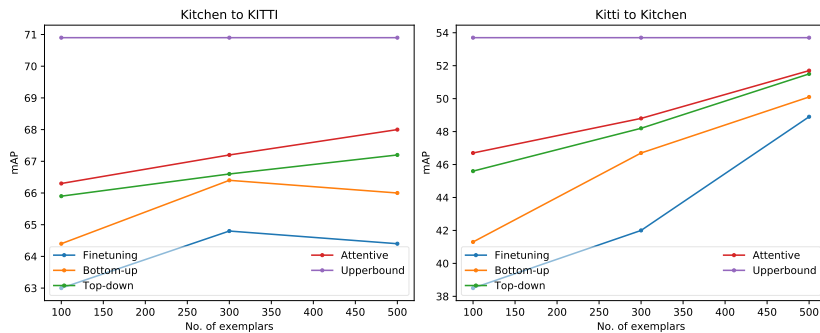
### 5.3 Ablation Study

**Ablation study for different sampling methods** As shown in Table 6, we compare with the different sampling strategies introduced in Section 4.5. All results are reported with the proposed AFD. Hard sampling performs better than random sampling from Kitchen to KITTI, but is much worse from KITTI to Kitchen. When looking at the selected samples, we found that many consecutive frames have a very similar scene, which reduces the diversity of samples. By choosing different values of  $\eta$ , we observe that adaptive sampling outperforms both random and hard sampling with  $\eta = 5$  being the best and fixing it for the remaining experiments.

**Ablation study for number of exemplars** Although we have shown that AFD can mitigate forgetting by a large margin, there is still a gap with Joint Training in the more challenging scenario (i.e. KITTI - Kitchen). Therefore, we experiment with exemplar sampling by keeping a small number of exemplars from the previous task. As shown in Figure 7, it is notable that with only 100 randomly sampled exemplars, Fine-tuning

**Table 6.** Ablation study on different sampling methods. "Average" means the average of numbers in the same row for easy comparison.

method	samples	Kitchen $\rightarrow$ KITTI		KITTI $\rightarrow$ Kitchen		Average
none	0	20.5	50.5	36.6	72.0	44.9
random	100	66.3	53.8	46.7	73.1	60.0
hard	100	69.4	51.6	42.1	71.7	58.7
adaptive ( $\eta=3$ )	100	68.1	52.5	45.9	71.4	59.5
adaptive ( $\eta=5$ )	100	68.6	53.4	48.4	72.0	<b>60.6</b>
adaptive ( $\eta=7$ )	100	67.8	52.6	48.1	72.4	60.2
adaptive ( $\eta=9$ )	100	67.3	53.2	47.2	72.7	60.1

**Fig. 7.** Ablation study on different number of exemplars. Evaluation on the first dataset after training on the second dataset.

increases by  $\sim 50\%$  from Kitchen to KITTI, and by  $\sim 25\%$  from KITTI to Kitchen. Combined with our distillation methods, the accuracy from previous task gets closer to Joint Training. Performance improves as more exemplars are added. AFD is superior to both individual bottom-up and top-down attentions.

## 6 Conclusion

In this paper, we study the problem of multi-task incremental detection by decomposing the two-task case into four different scenarios. With the proposed attentive feature distillation (AFD) on the three non-trivial scenarios, we gain insights on how domain gaps and category differences impact forgetting. Specifically, in our experiments, domain gaps cause less forgetting, and the category differences are actually the bigger problem (See Section 4.4). In these difficult cases, we need to adaptive sample a small number of exemplars from the previous tasks to mitigate forgetting.

There are several different directions we can explore in future works. We can dive deep into quantifying the backbone feature differences between different scenarios to gain further understanding of why category differences have larger impact than domain gaps. We will extend our work to one-stage detectors, such as YOLO [34], for higher efficiency. For more tasks cases, we need to understand more on whether network capacity is the bottleneck and if we need distill multiple levels of features.

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