Curriculum Self-Paced Learning for Cross-Domain Object Detection

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Abstract

Training (source) domain bias affects state-of-the-art object detectors, such as Faster R-CNN, when applied to new (target) domains. To alleviate this problem, researchers proposed various domain adaptation methods to improve object detection results in the cross-domain setting, e.g. by translating images with ground-truth labels from the source domain to the target domain using Cycle-GAN or by applying self-paced learning. On top of combining Cycle-GAN transformations and self-paced learning, in this paper, we propose a novel self-paced algorithm that learns from easy to hard. To estimate the difficulty of each image, we use the number of detected objects divided by their average size. Our method is simple and effective, without any overhead during inference. It uses only pseudo-labels for samples taken from the target domain, i.e. the domain adaptation is unsupervised. We conduct experiments on two cross-domain benchmarks, showing better results than the state of the art. We also perform an ablation study demonstrating the utility of each component in our framework.

1. Introduction

Machine learning models exhibit poor performance when the test (target) data are sampled from a different domain than the training (source) data due to the distribution gap (domain shift) between the different domains. Domain shift is a well-studied problem in the broad area of machine learning [3, 4, 14, 16, 28, 44, 45, 50, 59], attracting a lot of attention in computer vision [3, 14, 42, 44, 45, 47, 50, 51] and related fields [7, 13, 25, 37, 59]. To understand and address the domain gap, which occurs when labeled data in a target domain are scarce or not even available, researchers have studied the behavior of machine learning models in the cross-domain setting [15, 32] and proposed several domain adaptation methods [3, 13, 16, 42, 45, 47, 51].

Domain adaptation methods can be divided into supervised and unsupervised approaches. While supervised approaches use small subsets of labeled samples from the target domain [6, 23], the unsupervised ones use only unlabeled target samples [4, 16, 21, 40, 44, 46, 45, 51]. In this paper, we propose an unsupervised domain adaptation method for object detection. In cross-domain object detection [4, 28, 40, 44, 46, 58], an object detector is trained on data from a source domain and tested on data from a (different) target domain. Adapting the object detector for the cross-domain setting can provide the means to train robust models on very large scale datasets, that can be cheaply collected, but are outside the target domain. One such example is training object detectors for street scenes, e.g. Cityscapes [5], by using generated scenes from realistic video games, e.g. Sim10k [27]. We actually test our domain-adapted detector in this setting, which has immediate application in autonomous driving.

We propose a novel curriculum self-paced learning approach in order to adapt the object detector to the target domain. In self-paced learning, the model learns from its own predictions (pseudo-labels) in order to gain additional accuracy. Since we use image samples from the target domain during inference, the model has the opportunity to learn domain-specific features, thus is adapting itself to the target domain. However, the main problem in self-paced learning is that the model can be negatively influenced by the noisy pseudo-labels, i.e. prediction errors. In order to alleviate this problem, we employ two approaches. In order to reduce the labeling noise level we apply a domain-adaptation approach that relies only on ground-truth labels before the self-paced learning stage. The approach is to train a Cycle-consistent Generative Adversarial Network (Cycle-GAN) [57] in order to learn how to transform images from the source domain to the target domain. The adaptation consists in fine-tuning the object detector on source images that are translated by Cycle-GAN to look like target images. In the experiments, we show that reducing the labeling noise before self-paced learning is indeed helpful, but not enough. We believe the performance can be further improved by employing curriculum learning [1]. We hypothesize that the labeling noise inherently induced by the prediction errors is proportional to the difficulty of
Figure 1. Our curriculum self-paced learning approach for object detection. In the initial training stage (step 1.a), the object detector is trained on source images with ground-truth labels. In step 1.b, the object detector is further trained on source images translated by CycleGAN [57] to resemble images from the target domain. In steps 2, 3 and 4, the object detector is fine-tuned on real target images (different from those included in the test set), using the bounding boxes and the labels predicted by the current detector. In step 5, the model makes its predictions on the target test set for the final evaluation. Best viewed in color.

the images. In this case, we can perform self-paced learning starting with the easier images and gradually adding more difficult image samples, as shown in Figure 1. Our hypothesis turns out to be supported by the empirical results, confirming the utility of our curriculum self-paced learning method. In order to estimate the difficulty of each image sample, we employ a score given by the number of detected objects divided by the average area of their bounding boxes. This is inspired by the previous work of Ionescu et al. [24], which found that image difficulty is directly proportional to the number of objects and inversely proportional to the average bounding box area.

We evaluate our curriculum self-paced learning approach on two cross-domain benchmarks, Sim10k→Cityscapes and KITTI→Cityscapes, comparing it with several state-of-the-art methods [4, 28, 44, 46, 58]. The empirical results indicate that our approach provides the highest absolute gains (with respect to the baseline detector) on both benchmarks. In terms of Average Precision, we consider that our gains of +17.01% on Sim10k→Cityscapes and +13.18% on KITTI→Cityscapes are significant.

The rest of our paper is organized as follows. We present the related state of the art on domain adaptation, self-paced learning, curriculum learning and cross-domain object detection in Section 2. Our curriculum self-paced learning method is detailed in Section 3. The comparative and ablation experiments are presented in Section 4. Finally, we draw our conclusion and discuss future work in Section 5.

2. Related Work

Domain Adaptation. Domain adaptation is the task of fitting a model trained on a source distribution to a different target distribution. One immediate use case is the elimination of the costly human labeling process by automatically generating artificial training data, e.g. object detectors for autonomous driving could be trained on video game scenes. Domain adaptation has been extensively studied in cross-domain classification problems. The corresponding methods can be roughly categorized into cross-domain kernels [10, 25], sub-space alignment [14], second-order
statistics alignment [50], adversarial adaptation [16, 51], graph-based methods [3, 36, 37, 39], probabilistic models [33, 59], knowledge-based models [2, 15] and joint optimization frameworks [31]. To our knowledge, curriculum domain adaptation has not been extensively studied in literature [56]. Zhang et al. [56] proposed a curriculum domain adaptation method for semantic segmentation. They applied curriculum over tasks, starting with the easier ones, which are less sensitive to the domain gap than semantic segmentation. Different from Zhang et al. [56], we assign a difficulty score to each image sample, thus applying curriculum over samples. Furthermore, we employ Cycle-GAN as a way to reduce the labeling noise before our curriculum self-paced learning stage.

Curriculum Learning. Bengio et al. [1] introduced easy-to-hard strategies to train machine learning models, showing that the standard learning paradigm used in human educational systems also applies to artificial intelligence. Curriculum learning represents the general class of algorithms in which the training data are fed gradually, from easy-to-difficult, taking into consideration some difficulty measure. Curriculum learning has been successfully applied to different tasks, including semi-supervised image classification [19], language modeling [20], weakly-supervised object detection [53, 55], weakly supervised object localization [24, 30], person re-identification [52] and image generation [8, 48]. To our best knowledge, curriculum learning has not been applied to cross-domain object detection. In our work, we apply curriculum over target instances that are annotated with pseudo-labels given by the object detector at hand, resulting in a method that combines curriculum and self-paced learning.

Self-Paced Learning. In self-paced learning, machine learning models learn from their own labels while taking into consideration the predictions with high confidence first. Self-paced learning is similar to curriculum learning because the training samples are presented in a meaningful order. Kumar et al. [29] argued that their self-paced learning approach differs from curriculum learning, as it does not rely on an external difficulty measure, but on simultaneously selecting easy samples and updating the parameters in an iterative manner based on the actual performance. Jiang et al. [26] introduced self-paced curriculum learning as an optimization problem taking into account both prior knowledge and knowledge gained during the learning process. We propose a similar approach for a completely different task than Jiang et al. [26], namely cross-domain object detection. To our knowledge, we are the first to study curriculum self-paced learning in the cross-domain setting.

Cross-Domain Object Detection. While domain adaptation has been extensively studied for cross-domain classification, cross-domain object detection is a more challenging and less studied task, perhaps because it requires localizing each object in addition to the identification of object classes in an image. Inoue et al. [23] tackled the cross-domain weakly-supervised object detection task using a two-step progressive domain adaptation technique to fine-tune the detector trained on a source domain, while others [4, 28, 40, 44, 46, 58] studied unsupervised cross-domain object detection methods. We consider only the latter ones in the experiments, to make a fair comparison to our method. Raj et al. [40] used subspace alignment, a domain adaptation method consisting of learning a mapping from the source distribution to the target one. Chen et al. [4] argued that the gap between domains can be found both at the image level (illumination, style) and at the instance level (object size and overall appearance). Thus, they provided separate components to treat each case, on top of a Faster Region-based Convolutional Neural Network (R-CNN) [41] detector. These components use a domain classifier and adversarial training to learn domain-invariant features. Different from Raj et al. [40] and Chen et al. [4], we propose a curriculum self-paced learning approach to adapt the detector to the target domain.

Zhu et al. [58] proposed a framework that focuses on aligning the local regions containing objects of interest. It consists of a region mining component which finds relevant patches and a region-level alignment component which uses adversarial learning to align the image patches reconstructed from the features of the selected regions. Khodabandeh et al. [28] proposed a robust framework which takes into consideration the generated labels of the target domain to retrain the detector on both domains. The robustness is defined against mistakes in both object classification and localization. Thus, during retraining, the model can change labels and detection boxes, refining the noisy labels on the target domain. To improve the detections even further, the authors use a supplementary classification module, that provides information about the target domain. We propose a more simple and effective framework, that learns gradually from noisy pseudo-labels using an easy-to-hard approach.

Saito et al. [44] introduced an object detection framework that performs both strong local alignment and weak global alignment. Strong local alignment is obtained using a fully convolutional network with one-dimensional kernels as a local domain classifier trained to focus on local features. For the weak global feature alignment, the authors trained a domain classifier to ignore easy-to-classify examples while focusing on the more difficult ones, with respect to the domain classification. The reason behind this approach is that easy-to-classify target examples are far from the source in the feature space, while the harder examples are closer to the source. Different from Saito et al. [44], we do not use a domain classifier to determine which samples are easy and which are difficult. Instead, we estimate the difficulty at the image level by computing the number
of detected objects divided by their average bounding box area. This gives us a measure of difficulty from a different perspective, that of the object detector (not the one of the domain classifier). In our case, the object detector has higher accuracy for the easy image samples versus the difficult image samples.

Shan et al. [46] proposed a multi-module framework consisting of a pixel-level domain adaptation based on Cycle-GAN and a feature-level domain adaptation based on Faster R-CNN. The pixel-level alignment is achieved by using a traditional generator-discriminator GAN approach, with a loss function to ensure cycle consistency. In comparison, our method is a simple and straightforward combination of modules, adversarial domain adaption and curriculum self-paced learning, stacked on top of a traditional Faster R-CNN baseline. We use Cycle-GAN to transfer from the source training set to the target set, thus generating additional training (labeled) information with similar style to the target domain. We then extract pseudo-labels from an already more trustworthy detector, and fine-tune it through curriculum self-paced learning. Our novel idea is that fine-tuning can be done in a meaningful, not random, order, which is defined by our measure of image difficulty.

3. Method

Domain adaptation is a fervent topic, and many works on object detection already take advantage of adaptation methods to align models trained across domains [4, 28, 44, 46, 58]. The same consideration has been granted to self-supervised learning techniques, in which exploiting reliable pseudo-labels to improve classification has been already investigated [9, 35, 54]. In this work, however, we aim at evaluating a model which incorporates a domain adaptation method based on style transfer using GAN-like preprocessing in conjunction with a self-paced learning method based on difficulty-wise curriculum learning provided by the difficulty metric proposed in Section 3.1.

The general principle of the easy-to-hard training strategies known as curriculum learning [1], stems from the fact that human beings learn better when they receive easy examples first, with gradually more complex concepts being introduced later. Bengio et al. [1] proved this method to be effective for neural networks training as well. Inspired by Bengio et al. [1], we propose a novel method to apply curriculum learning to object detection, replacing the random sampling during self-paced training. At this point, an important question arises: “How to define the difficulty of detecting objects in an image?” Few different solutions have been proposed to this problem [24, 49, 53, 55]. However, in these works, the difficulty score has been computed on a large set of object classes, while we focus on a specific object class, car, so we opted for a different metric.

We show that fine-tuning the model with pseudo-labels increases performance. Nonetheless, in our experiments, we found it more impactful when pseudo-labels are used on top of a “warmed-up” model, because, in this way, our confidence in the generated labels will be higher. Our aim is building a simple and efficient method which can be used together with almost any other domain adaptation strategy, so we did not alter the architecture of the standard Faster R-CNN [41] detector, nor used any other complex adaptation strategy. In order to reduce pseudo-labeling noise (increasing the performance by as much as possible) before applying fine-tuning on real target images, we translate the source images to the target domain using Cycle-GAN, then train on the resulting images together with the original source training set, thus warming-up the model before curriculum self-paced learning.

In the rest of this section, we briefly present the components employed in our framework and detail our algorithm.

3.1. Components

Faster R-CNN. Faster R-CNN [41] is one of the state-of-the-art region-based deep detection models. It is a two-stage object detector which improves Fast R-CNN [18] by introducing the Region Proposal Networks. In order to select the right regions of interest, it uses a fully convolutional network that can predict object bounds at every location. The selected regions are then, in the second stage, provided as an input to the Fast R-CNN model, which gives the final detection results.

Cycle-GAN. Cycle-GAN [57] is a generative model performing image translation between two domains without requiring paired images for training. It learns the relevant features and the translation mapping by using cycle consistency, constraining the model so that translating from one domain to another and back again must reach the starting point.

Difficulty Metric. In [24, 49], the authors suggest that images containing many small objects are more difficult than samples with few large objects. Thus, one could compute an image difficulty score as the number of detected objects divided by their average bounding box size. Given a set of $n$ bounding box detections $B = \{b_1, b_2, ..., b_n\}$ in an image $I$, where a detection $b_i$ is composed of a tuple $(x_i, y_i, w_i, h_i)$ representing the coordinates of the top left corner $(x_i, y_i)$, the width and the height of the bounding box, we define our difficulty scoring function $S$ as follows:

$$S(I, B) = \frac{1}{n} \sum_{i=1}^{n} w_i \cdot h_i = \sum_{i=1}^{n} \frac{n^2}{w_i \cdot h_i}. \quad (1)$$

This method is effective in our case, because it computes difficulty as a function of the detected instances. Since in our data sets we only evaluate on the car class, other objects that appear in the image do not affect the ranking. More general difficulty measures, such as the one proposed by
Algorithm 1: Our cross-domain object detection algorithm

| Line | Description |
|------|-------------|
| 1    | **Input:** |
| 2    | $X_s$ – the source data set of samples; |
| 3    | $Y_s$ – the ground-truth labels for source data $X_s$; |
| 4    | $X_t$ – the target training set of unlabeled samples; |
| 5    | $X_t^{(test)}$ – the target test set, where $X_t \cap X_t^{(test)} = \emptyset$; |
| 6    | $S$ – a difficulty scoring function, e.g. Equation (1); |
| 7    | $k$ – the number of batches to split by difficulty; |
| 8    | **Notations:** |
| 9    | $D$ – an object detector, e.g. Faster R-CNN; |
| 10   | $T$ – an image translation model, e.g. Cycle-GAN; |
| 11   | $\tilde{X}_s$ – the generated images with target domain style; |
| 12   | $\tilde{Y}_t$ – the pseudo-labels for target data $X_t$; |
| 13   | **Computation:** |
| 14   | $T \leftarrow train(T/X_s, X_t)$; |
| 15   | $\tilde{X}_s \leftarrow T(X_s)$; |
| 16   | $D \leftarrow train(D/(X_s, Y_s) \cup (\tilde{X}_s, Y_s))$; |
| 17   | for $i \leftarrow 1, k$ do |
| 18   | $\tilde{Y}_t \leftarrow D(X_t)$; |
| 19   | $X_t^{(1)}, ..., X_t^{(k)}, Y_t^{(1)}, ..., Y_t^{(k)} \leftarrow split(X_t, \tilde{Y}_t, k, S)$; |
| 20   | $D \leftarrow train(D/\bigcup_{j=1}^{k}(X_t^{(j)}, Y_t^{(j)}))$; |
| 21   | $B \leftarrow D(X_t^{(test)})$; |
| 22   | **Output:** |
| 23   | $B$ – the set of predicted bounding boxes. |

Ionescu et al. [24], take into consideration all object classes. It is important to note that the extreme case of images without any detected objects is considered hard.

3.2. Algorithm

We next explain our algorithm, as illustrated in Figure 1 and formally presented in Algorithm 1. Our algorithm is split in two phases: the first one for the warm-up of the detector $D$ (steps 14-16) and the second for the self-paced refinement (steps 17-20).

In our warm-up phase, we randomly sample a subset from both data sets and train a Cycle-GAN to generate a set of samples $\tilde{X}_s$ with an appearance similar to the target, but with labels $Y_s$ inherited from the source. Using samples generated by the Cycle-GAN, we perform a traditional supervised training on the source domain using an out-of-the-box Faster R-CNN model (step 16). By mixing samples from the source domain with samples generated by Cycle-GAN, we produce a model that favors the alignment between the two domains, helping the self-paced learning on the unlabeled pristine target data set $X_t$.

The second phase is an iterative process described in steps 17 to 20 in Algorithm 1. At each iteration $i$, we first apply the current object detector $D$ on the target samples $X_t$ to produce the pseudo-labels $\tilde{Y}_t$. The target samples are then ranked according to the proposed difficulty metric and divided in $k$ batches difficulty-wise, i.e. according to Equation 1. Finally, the first $i$ batches, starting from those ranked as easier, are used for training the object detector $D$. The curriculum self-paced learning process is repeated until eventually the whole target set has been included in the training process. It is important to note that only the high confidence detections have been taken in consideration, performing a threshold-based selection.

The intuition behind the usage of this curriculum fine-tuning approach over the standard random one relies on the simple fact that pseudo-labels for easier samples are more accurate. By using less difficult samples first, we can reduce the domain gap without learning too many wrongly detected objects. In this way, most pseudo-labels, even those of the harder samples, will be trustworthy, leading to higher performance after the final retraining step.

4. Experiments

4.1. Data Sets

Following the methodology of previous studies [4, 28], we apply our method on three street scenes data sets: Sim10k [27], KITTI [17] and Cityscapes [5], considering only their common class, i.e. car. Sim10k is a computer-generated data set of 10,000 images with traffic scenes, which we use as the source for our simulated to real domain transfer. KITTI is another driving data set consisting of 7,481 real training images that we use as source in our experiments which involve adaptation between two real data sets. Cityscapes contains 2,945 training images and 500 validation images of urban scenes. In our experiments, we use the training set (with pseudo-labels) for self-paced learning and the validation set for testing and evaluation.

4.2. Experimental Setup

Evaluation Measure. The performance of object detectors on a class of objects is typically evaluated using the Average Precision, which is based on the ranking of detection scores [12]. We thus report the AP on the car class. The AP score is given by the area under the precision-recall (PR) curve for the detected objects. The PR curve is constructed by first mapping each detected bounding box to the most-overlapping ground-truth bounding box, according to the Intersection over Union (IoU) measure, but only if the IoU is higher than 0.5 [11]. Then, the detections are sorted in decreasing order of their scores. Precision and recall values are computed each time a new positive sample is recalled. The PR curve is given by plotting the precision and recall pairs as lower-scored detections are progressively included.

Baselines. In order to show the relevance of our approach, we compare our results with several state-of-the-art methods [4, 28, 44, 46, 58]. The approach of Chen et al. [4]
### Implementation Details

In our experiments, we employ Faster R-CNN \cite{FRCNN} built on the ResNet50 \cite{ResNet} architecture as our object detector. We use the PyTorch \cite{PyTorch} implementation of Faster R-CNN from \cite{FRCNN} with weights pre-trained on ImageNet \cite{ImageNet}. We perform image translation using the Cycle-GAN \cite{CycleGAN} implementation available at https://github.com/arnab39/cycleGAN-PyTorch. We train Cycle-GAN for 200 epochs and Faster R-CNN for 50,000 iterations, using an adaptive learning rate. At the end of the training, we generate the pseudo-labels and apply self-paced learning for 500 iterations, with new training labels being generated at every 100 iterations. In the curriculum self-paced learning setup, we use easy images for the first 50 iterations, easy and medium images for the next 50 iterations, and the whole data set (including easy, medium, and hard images) for the remaining iterations. The number of batches used in Algorithm 1 is \( k = 3 \).

### 4.3. Preliminary Results

We conduct a preliminary set of experiments to validate our hypothesis stating that the number of objects divided by their average bounding box area is a good measure of image difficulty in the context of object detection. We first train the Faster R-CNN on original source images and on images translated by Cycle-GAN. The model is thus already adapted to the target domain and should provide more reliable labels on real target images. We next apply the model on target domain images and we divide the images into \( k = 3 \) batches, in increasing order of difficulty. We provide the corresponding results on both benchmarks in Table 1. We note that the AP scores on the easy batch of images are higher than the AP scores on the medium batch. We observe the same behavior on the medium batch with respect to the hard batch. In conclusion, the empirical results presented in Table 1 confirm our hypothesis. We can thus apply the proposed difficulty measure in our curriculum self-paced learning approach.

| Data Set       | Easy   | Medium | Hard   |
|----------------|--------|--------|--------|
| Sim10k→Cityscapes | 44.43  | 43.51  | 36.90  |
| KITTI→Cityscapes    | 40.70  | 40.05  | 38.08  |

Table 1. Average Precision (AP) scores for easy, medium and hard image batches, provided by Faster R-CNN trained on original source images and on images translated by Cycle-GAN. Results are reported for Sim10k→Cityscapes and KITTI→Cityscapes benchmarks.

minimizes image-level and instance-level domain shift using two components based on the \( H \)-divergence theory and adversarial training. The method of Zhu et al. \cite{Zhu} aligns local regions that contain objects of interest, using a region mining component to find relevant patches. The framework of Khodabandeh et al. \cite{Khodabandeh} uses the generated labels on the target domain to retrain the detector on both domains. Their method benefits from a supplementary classification module that provides information about the target domain. The framework of Saito et al. \cite{Saito} tackles the adaptation problem by using strong local alignment and weak global alignment. The model of Shan et al. \cite{Shan} consists of two modules: a pixel-level domain adaptation based on Cycle-GAN and a feature-level domain adaptation based on Faster R-CNN. Along with the best scores reported by each of these state-of-the-art methods, we also include the baseline detection models (without adaptation), observing the absolute gain in performance provided by each domain adaptation method with respect to the corresponding baseline.

### 4.4. Cross-Domain Detection Results

We compare our domain adaptation method with several state-of-the-art approaches \cite{Cao, Khodabandeh, Zhu, Zhu} on Sim10k→Cityscapes and KITTI→Cityscapes benchmarks. We provide the comparative object detection results in Table 2.

First, we note that each related method is build on top of a slightly different Faster R-CNN baseline (trained on source only). While two methods \cite{Shan, Zhu} start from somewhat-better Faster R-CNN versions, our Faster R-CNN baseline gives similar AP scores to the Faster R-CNN baselines used in \cite{Cao, Zhu}. Since the baselines are not equally good, we report the absolute gains with respect to the corresponding baseline along with the AP scores, for a more fair comparison between the domain adaptation methods.

On Sim10k→Cityscapes, we obtain the best AP score (47.68%) as well as the largest improvement over the baseline (17.01%). In terms of AP, the second best result, reported by Zhu et al. \cite{Zhu}, is 4.66% lower. The improvement of Zhu et al. \cite{Zhu} over their baseline is however much lower (9.06%). In terms of absolute gain over the corresponding baseline, the second best method is that of Khodabandeh et al. \cite{Khodabandeh}. Our absolute gain is 5.53% higher than that of Khodabandeh et al. \cite{Khodabandeh}. We conclude that our domain-adaptation method attains significant improvements over the state-of-the-art methods on the Sim10k→Cityscapes benchmark.

On KITTI→Cityscapes, we obtain the second best AP score (42.93%), with only a very small margin (0.06%) below the best state-of-the-art method \cite{Khodabandeh}. Nevertheless, we should point out that Khodabandeh et al. \cite{Khodabandeh} start from a better Faster R-CNN baseline. Hence, our absolute gain (13.18%) is higher than the absolute gain (11.88%) of Khodabandeh et al. \cite{Khodabandeh}. The other methods from the recent literature \cite{Cao, Zhu, Zhu, Khodabandeh} attain lower results in terms of AP scores as well as absolute gains. We conclude that, at least in terms of absolute gain, our method is better than all other methods on KITTI→Cityscapes.
### 4.5. Ablation Study

We conduct an ablation study to determine the benefits of each individual component in our framework. Table 3 illustrates our results on both cross-domain benchmarks, indicating the contribution of each component to the overall AP score.

#### Source→Target Translation with Cycle-GAN. Starting from the Faster R-CNN baselines with AP scores of around 30% (30.67% for Sim10k→Cityscapes and 29.75% for KITTI→Cityscapes), we gain almost 11% and 8%, respectively. We observe that training on images translated from KITTI to Cityscapes is less effective. We suspect that the gap between synthetic (Sim10k) and real data (Cityscapes) can be easier to bridge than the gap induced by different cameras and object sizes/view angles between data sets containing real scenes (KITTI and Cityscapes). Another aspect worth mentioning here is that the results obtained using Cycle-GAN translations on Sim10k are quite close to the state-of-the-art.

#### Self-Paced Learning. We employ self-paced learning from pseudo-labels either on top of the model trained only on source data or on top of the model trained with additional data produced via Cycle-GAN translation. We can see in both cases a constant increase in performance of around 4%. From the results, we conclude that self-paced learning alone does not reach the performance gains of the Cycle-GAN adaptation approach, with a difference of 7% on Sim10k→Cityscapes and 3% on KITTI→Cityscapes. Still, the accuracy improvement is also visible on the model that is already trained using translation, supporting our decision to perform self-paced learning on top of Cycle-GAN adaptation.

#### Curriculum Self-Paced Learning. Our best results are
Figure 2. Examples of detected cars provided by the baseline Faster R-CNN (first row) versus detections provided by two ablated versions of our framework (second and third rows) and our full domain adaptation framework based on Cycle-GAN and curriculum self-paced learning (fourth row). Samples are selected from both Sim10k $\rightarrow$ Cityscapes (first three columns) and KITTI $\rightarrow$ Cityscapes (last three columns) experiments. Green bounding boxes represent correct detections; red bounding boxes represent false positives; blue bounding boxes represent false negatives. Best viewed in color.

not obtained, though, using basic self-paced learning, but using a curriculum learning approach in which the fine-tuning is conducted by gradually adding more difficult image batches. Our results show a gain of around 1 – 2% over standard self-paced learning. Although curriculum self-paced learning alone does not provide results as good as Cycle-GAN translation when applied on the baseline model (trained only on source), the complete framework, with all the components in place, provides state-of-the-art results. Another benefit of our curriculum learning approach over the standard one is that it provides more stable results, and the results can be easily replicated under random initialization or different self-paced learning settings.

Qualitative Analysis. Figure 2 illustrates some typical detection results of the baseline Faster R-CNN versus our framework. Object detections provided by ablated versions of our framework are also included. In general, we observe that the domain-adapted models are able to detect more cars (depicted inside green bounding boxes in Figure 2), i.e. the number of false negatives (blue bounding boxes in Figure 2) is reduced. In the same time, the domain-adapted models give more false positives (red bounding boxes in Figure 2). It seems that the self-paced learning framework applied after Cycle-GAN adaptation (third row in Figure 2) has more false positives than the other domain adaptation methods (second and fourth rows in Figure 2).

5. Conclusion

In this paper, we presented a domain adaptation method for cross-domain object detection. Our method is based on two adaptation stages. First of all, images translated from the source domain to the target domain using Cycle-GAN are added into the training set. Second of all, a curriculum self-paced learning approach is employed to further adapt the object detector using real target images annotated with pseudo-labels. We compared our method with several state-of-the-art-methods [4, 28, 44, 46, 58] and we obtained higher absolute performance gains with respect to the corresponding Faster R-CNN baselines. Although we attained better results than those reported in the recent literature [4, 28, 44, 46, 58], we notice that there are still significant performance gaps with respect to the Faster R-CNN models that are trained on the target domain with ground-truth labels (see Table 2). We believe that the performance gap can be further reduced by training on multiple source domains. Data augmentation after pseudo-labeling could also play an important role in gaining additional performance. We aim to explore these directions in future work.

Acknowledgements. Work funded from a grant of Ministry of Research and Innovation, CNCS-UEFISCDI, project no. PN-III-P1-1.1-PD-2016-0787, and from the EEA Grants 2014-2021, project no. EEA-RO-NO-2018-0496.
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