Pedestrian Detection: The Elephant In The Room

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Abstract. Pedestrian detection is used in many vision based applications ranging from video surveillance to autonomous driving. Despite achieving high performance, it is still largely unknown how well existing detectors generalize to unseen data. To this end, we conduct a comprehensive study in this paper, using a general principle of direct cross-dataset evaluation. Through this study, we find that existing state-of-the-art pedestrian detectors generalize poorly from one dataset to another. We demonstrate that there are two reasons for this trend. Firstly, they over-fit on popular datasets in a traditional single-dataset training and test pipeline. Secondly, the training source is generally not dense in pedestrians and diverse in scenarios. Accordingly, through experiments we find that a general purpose object detector works better in direct cross-dataset evaluation compared with state-of-the-art pedestrian detectors and we illustrate that diverse and dense datasets, collected by crawling the web, serve to be an efficient source of pre-training for pedestrian detection. Furthermore, we find that a progressive training pipeline works good for autonomous driving oriented detector. We improve upon previous state-of-the-art on reasonable/heavy subsets of CityPersons dataset by 1.3%/1.7% and on Caltech by 1.8%/14.9% in terms of log average miss rate ($MR^{-2}$) points without any fine-tuning on the test set. Detector trained through proposed pipeline achieves top rank on the leaderboards of CityPersons [42] and ECP [4]. Code and models will be available at https://github.com/hasanirtiza/Pedestron.

Keywords: Pedestrian Detection, Autonomous Driving, Video Surveillance, Transfer Learning and Robotics

1 Introduction

Pedestrian detection is a very actively researched task in the computer vision community, both in academia and industry. It has applications in many different domains, including robotics and autonomous vehicles, entertainment, and smart

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Pedestrian detection also plays a critical role in various other computer vision research areas, such as multi-object tracking, human pose estimation, person identification/search, etc. Advances in pedestrian detection systems potentially can dramatically improve the performance and robustness of these systems, which in some cases (e.g. accident avoidance in autonomous vehicles) may even save human lives.

Pedestrian detection is a very challenging problem due to huge variations in pedestrian appearance arising from their scale, pose, clothing, motion blur, illumination (e.g. night-time), surroundings, occlusion and the presence of confounders (e.g. advertisements, reflections). Occlusion and small-scale are the two most important challenges limiting the performance of current detectors, and they are responsible for most failures.

Fig. 1 left, shows the recent progress on three major pedestrian detection datasets. Deep learning has led to a dramatic improvement in the performance of pedestrian detectors in recent years. However, Some current pedestrian detection methods show signs of over-fitting to source datasets especially in the case of autonomous driving as shown in Fig. 1 right, as they do not generalize well to other (target) pedestrian detection datasets, even when trained on a relatively large scale dataset which is reasonably closer to the target domain.

There may be two reasons for this trend. Firstly, in the traditional single-dataset training and test pipeline, the current state-of-the-art pedestrian detectors are tailored for target datasets and their overall design may contain biasness.
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Towards target datasets, thus reducing their generalization. Secondly, the training source is generally not dense in pedestrians and diverse in scenarios. Since current state-of-the-art methods are based on deep learning, their performance depend heavily on the quantity and quality of data and there is some evidence that the performance on some computer vision tasks (e.g. image classification) keeps improving at least up-to billions of samples [24]. Pedestrian detection research community has in recent years published increasingly bigger and more challenging datasets [32, 33, 41] to advance the field. Although the size of these datasets has increased by several orders of magnitude, the data still remains one of the major bottleneck in the performance of these methods [4]. At present, all autonomous driving related datasets have at least three main limitations, 1) limited number of unique pedestrians, 2) low pedestrian density, i.e. the challenging occlusion samples are relatively rare, and 3) limited diversity as the datasets are captured by a small team primarily for dataset creation instead of curating them from more diverse sources (e.g. youtube, facebook, etc.).

In last couple of years, two large and diverse datasets, CrowdHuman [31] and Wider Pedestrian [1], have been collected by crawling the web. These datasets address the above mentioned limitations but as they are from a much broader domain, they do not sufficiently cover autonomous driving scenarios. Nevertheless, they can still be very valuable for learning a more general and robust model of pedestrians, which is beneficial for autonomous driving scenarios.

In this paper, we demonstrate that the existing pedestrian detection methods fare poorly compared to general object detectors when provided with larger and more diverse datasets, and that the state-of-the-art general detectors when carefully trained can significantly out-perform pedestrian-specific detection methods on pedestrian detection task, without any pedestrian-specific adaptation on the target data (see Fig. 1 right). We also propose a progressive training pipeline for better utilization of general pedestrian datasets for improving the pedestrian detection performance in case of autonomous driving. We show that by progressively fine-tuning the models from the largest (but farthest away from the target domain) to smallest (but closest to the target domain) dataset, we can achieve large gains in performance in terms of $MR^{-2}$ on reasonable/heavy subset of Caltech (3.24%/20.86%), CityPerson (3.5%/15.4%) and EuroCityPerson (1.8%/10.9%). These improvement hold true for models from all pedestrian detection families that we tested such as Cascade R-CNN, and MobileNet.

The rest of the paper is organized as follows. Section 2 reviews the relevant literature. We introduce datasets and evaluation protocol in Sec. 3. We benchmark our baseline in Sec. 4. We test the generalization capabilities of the baseline in Sec. 5. We discuss about current state-of-the-art along Section 6 and finally, conclude the paper in Section 7.

2 Related Work

**Pedestrian detection.** Before the emergence of CNNs, a common way to address this problem was to exhaustively operate in a sliding window manner over
all possible locations and scales, inspired from Viola and Jones [35]. Dalal and Triggs in their landmark pedestrian detection work [10] proposed Histogram of Oriented Gradients (HOG) feature descriptor for representing pedestrians. Dollar et al [11], proposed ACF, where the key idea was to use features across multiple channels. Similarly, [12,27], used filtered channel features and low-level visual features along with spatial pooling respectively for pedestrian detection. These earlier works focused more on feature descriptors and mostly used either SVM [9] or random-forest for classification. Some works also tried to incorporate extra information such as motion [29] for pedestrian detection in videos. In all of the channel-based feature descriptors, the overlying idea was to extract features across multiple channels. However, the use of engineered features meant very limited generalization ability and limited performance.

In recent years, Convolutional Neural Networks (CNNs) have become the dominant paradigm in generic object detection [30,16,33,21]. The same trend is also true for the pedestrian detection [21,7]. Some of the pioneer works for CNN based pedestrian detection [17,41] used R-CNN framework [15], which is still the most popular framework. RPN+BF [40] was the first work to use Region Proposal Network (RPN); it used boosted forest for improving pedestrian detection performance. This work also pointed out some problems in the underlying classification branch of Faster RCNN [30], namely that the resolution of the feature maps and class-imbalance. However, RPN+BF despite achieving good performances had a shortcoming of not being optimized in a closed form. After the initial works, Faster RCNN [30] became most popular framework with wide range of literature deploying it for pedestrian detection [44,12,5,35,25].

Some of the recent state-of-the-art pedestrian detectors include ALF [22], CSP [23] and MGAN [28]. ALF [22] is based on Single Shot MultiBox Detector (SSD) [21], it stacks together multiple predictors to learn a better detection from default anchor boxes. MGAN [28] uses the segmentation mask of the visible region of a pedestrian to guide the network attention and improve performance on occluded pedestrians. CSP is an anchor-less fully convolutional detector, which utilizes concatenated feature maps for predicting pedestrians.

**Pedestrian detection benchmarks.** Over the years, several datasets for pedestrian detection have been created such as Town Center [3], USC [39], Daimler-DB [26], INRIA [10], ETH [13], and TUDBrussels [38]. All of the aforementioned datasets were typically collected for surveillance application. For example, the Town Center [3] dataset was recorded in city center with the fixed camera. USC [39] dataset focused on small scale pedestrian from the prospect of surveillance etc. None of these datasets were created with the aim of providing large-scale images for the autonomous driving systems. However, in the last decade several datasets have been proposed from the context of autonomous driving such as KITTI [14], Caltech [12], CityPersons [42] and ECP [4]. Typically these datasets are captured by a vehicle-mounted camera navigating through crowded scenarios. These datsets have been used by several methods with Caltech [12] and CityPersons [42] being the most established benchmarks in this domain. However, Caltech [12] and CityPersons [42] datasets are monotonous in nature and
they lack diverse scenarios (contain only street view images). Recently, ECP [4] dataset which is an order of magnitude larger than CityPersons [42] has been proposed. ECP [4] is much bigger and diverse, since it contains images from all seasons in several different countries and under both day and night times. However, despite its large scale, ECP [4] provides a limited diversity (in terms of scene and background) and density (number of people per frame is less than 10). Therefore, in this paper we argue that despite some recent large scale datasets, the ability of pedestrian detectors to generalize has been constrained by lack of diversity and density. Moreover, benchmarks such as Wider Pedestrian [1] and CrowdHuman [31], which contain web crawled images provide a much larger diversity and density. This enables detectors to learn a more robust representation of pedestrians with increased generalization ability.

3 Experiments

3.1 Experimental Settings

Datasets. We thoroughly evaluate and compare against state-of-the-art on three large-scale pedestrian detection benchmarks. These benchmarks are recorded from the context of autonomous driving, we refer to them as autonomous driving datasets. The Caltech [12] dataset has around 13K persons extracted from 10 hours of video recorded by a vehicle in Los Angeles, USA. All experiments on Caltech [12] are conducted using new annotations provided by [41]. CityPersons [42] is a more diverse dataset compared to Caltech as it is recorded in 27 different cities of Germany and neighboring countries. CityPersons dataset has roughly 31k annotated bounding boxes and its training, validation and testing sets contain 2975, 500, 1575 images, respectively. Finally, EuroCity Persons (ECP) [4] is a new pedestrian detection dataset, which surpasses Caltech and CityPersons in terms of diversity and difficulty. It is recorded in 31 different cities.

Table 1: Datasets statistics. ‡ Fixed aspect-ratio for bounding boxes.

|                  | Caltech | CityPersons | ECP  | CrowdHuman | Wider Pedestrian | COCO persons |
|------------------|---------|-------------|------|------------|------------------|--------------|
| images           | 42,782  | 2,975       | 21,795 | 15,000     | 30,000           | 64,115       |
| persons          | 13,674  | 19,238      | 201,323 | 339,565    | 287,131          | 257,252      |
| persons/image    | 0.32    | 0.64        | 9.2   | 22.64      | 3.2              | 4.01         |
| unique persons   | 1,273   | 19,238      | 201,323 | 339,565    | 287,131          | 257,252      |

Table 2: Experimental settings.

| Setting   | Height   | Visibility |
|-----------|----------|------------|
| Reasonable| [50, inf]| [0.65, inf]|
| Small     | [50, 75] | [0.65, inf]|
| Heavy     | [50, inf]| [0.2, 0.65]|
| Heavy*    | [50, inf]| [0.0, 0.65]|
| All       | [20, inf]| [0.2, inf]|

Wider Pedestrian [1] and CrowdHuman [31] provide a much larger diversity and density.
across 12 countries in Europe. It has images for both day and night-time (thus referred to as ECP day-time and ECP night-time). Total annotated bounding-boxes are over 200K. As mentioned in ECP [4], for the sake of comparison with other approaches, all experiment and comparisons are done on the day-time ECP. We report results on the validation set of ECP [4] unless stated otherwise. Evaluation server is available for the test set and frequency submissions are limited. Finally, in our experiments we also include two non-traffic related recent datasets namely, CrowdHuman [31] and Wider Pedestrian [1]. Collectively we refer to Caltech, CityPersons and ECP as autonomous driving datasets and CrowdHuman, Wider Pedestrian as web-crawled datasets. Details of the datasets are presented in Table 1.

Evaluation protocol. Following the widely accepted protocol of Caltech [12], CityPersons [42] and ECP [4], the detection performance is evaluated using log average miss rate over False Positive Per Image (FPPI) ranging in $[10^{-2}, 10^0]$ denoted by ($MR^{-2}$). We evaluate and compare all methods using similar evaluation settings. We report numbers for different occlusion levels namely, Reasonable, Small, Heavy, Heavy* and All unless stated otherwise. All of these settings represent different visibility/occlusion level. Similar to previous works such as Caltech [12], CityPersons [42] and ECP [4], pedestrians having height greater than 50 pixels are considered except for All occlusion setting. Visibility level for each setting is reported in Table 2.

Baseline. Since most of the top ranked methods on Caltech, CityPersons and ECP are direct extension of Faster/Mask R-CNN [30,16] family, we also select recent Cascade R-CNN [8] (an extension of R-CNN family) as our baseline. Cascade R-CNN contains multiple detection heads in a sequence, which progressively try to filter out harder and harder false positives. We choose HRNet [36] as our backbone-network because it retains feature maps at higher resolution, reducing the likelihood of important information being lost in repeated down-sampling and up-sampling, which is especially beneficial for pedestrian detection where the most difficult samples are very small.

4 Benchmarking

First, we present the benchmarking of our baseline on three autonomous driving datasets. Table 3 presents benchmarking on Caltech [12] dataset, Table 4 on CityPersons [42] and Table 5 on ECP [4] respectively. In the case of Caltech and CityPersons, our baseline without “bells and whistles” performs comparable to the existing state-of-the-art, which are tailored for pedestrian detection tasks.

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3 Wider Pedestrian has images from surveillance and autonomous driving scenarios. In our experiments, we used the data provided in 2019 challenge. Data can be accessed at: https://competitions.codalab.org/competitions/20132

4 In the case of CityPersons, under Heavy* occlusion the visibility level is $[0.0,0.65]$, for the sake of comparison with previous approaches, we used the same visibility level.
Its performance has a greater improvement compared to other methods with increasing dataset size. Its relative performance is worst on the smallest dataset (Caltech) and best on the largest dataset (EuroCityPersons).

5 Generalization Capabilities

5.1 Cross Dataset Evaluation of Existing State-of-the-Art

To see how well state-of-the-art pedestrian detectors generalize to different datasets, we performed cross dataset evaluation of three state-of-the-art pedestrian detectors and our baseline on CityPersons [42] and Caltech [12] datasets. We evaluated recently proposed CSP [23], ALFNet [22] and FRCNN [42] (tailored for pedestrian detection). Furthermore, we added along with our baseline, Faster R-CNN [30], without “bells and whistles”. We present results for Caltech and CityPersons in Table 6, respectively. Last column Reasonable* reports results when training is done on target dataset for readability purpose. For our results presented in top half of the Table 6, we trained each detector on CityPersons dataset and tested on Caltech dataset. Similarly, in the bottom half of the Table 6, all detectors were trained on the Caltech and evaluated on CityPersons benchmark.

5 Detailed baseline performances of each method can be seen in Table 13 and 15.

Table 3: Benchmarking: Caltech.

| Method      | Reasonable | Small | Heavy |
|-------------|------------|-------|-------|
| ALFNet [22] | 6.1        | 7.9   | 51.0  |
| Rep Loss    | 5.0        | 5.2   | 47.9  |
| CSP [23]    | 5.0        | 6.8   | 46.6  |
| Baseline    | 6.2        | 7.4   | 55.3  |

Table 4: Benchmarking: CP.

| Method      | Reasonable | Small | Heavy |
|-------------|------------|-------|-------|
| Rep Loss    | 13.2       | -     | -     |
| ALFNet      | 12.0       | 19.0  | 48.1  |
| CSP [23]    | 11.0       | 16.0  | 39.4  |
| Baseline    | 11.21      | 14.01 | 37.07 |

Table 5: Benchmarking: ECP Test set.

| Method       | Reasonable | Small | Heavy |
|--------------|------------|-------|-------|
| Faster R-CNN | 7.3        | 16.6  | 52.0  |
| YOLOv3       | 8.5        | 17.8  | 37.0  |
| SSD          | 10.5       | 20.5  | 42.0  |
| Baseline     | 6.6        | 13.6  | 33.3  |
Table 6: Cross dataset evaluation on Caltech and CityPerson. *Reasonable* refers to experiment where training and testing sets come from same dataset.

| Method     | Training | Testing | Reasonable | Reasonable* |
|------------|----------|---------|------------|-------------|
| FRCNN [42] | CityPersons | Caltech | 21.1       | 8.7         |
| ALFNET [22] | CityPersons | Caltech | 17.8       | 6.1         |
| CSP [23]   | CityPersons | Caltech | 12.1       | 5.0         |
| Faster R-CNN [30] | CityPersons | Caltech | 11.8       | 9.7         |
| Baseline   | CityPersons | Caltech | 8.8        | 6.2         |
| FRCNN [42] | Caltech | CityPersons | 46.9 | 15.4 |
| ALFNET [22] | Caltech | CityPersons | 47.29 | 12.0 |
| CSP [23]   | Caltech | CityPersons | 43.7  | 11.0 |
| Faster R-CNN [30] | Caltech | CityPersons | 40.8  | 16.4 |
| Baseline   | Caltech | CityPersons | 36.5  | 11.2 |

As expected, all methods suffer a performance drop when trained on CityPersons and tested on Caltech. Particularly, CSP [23], ALFNet [22] and FRCNN [42] degraded by more than 100% drop in performance (in comparison with last column). Whereas in the case of our baseline, performance remained comparable to the model trained and tested on target set. Since, CityPersons is a relatively diverse and dense dataset in comparison with Caltech, this performance deterioration cannot be linked to dataset scale and crowd density. This illustrates better generalization ability of our baseline over state-of-the-art pedestrian detectors. Importantly, standard Faster R-CNN [30], though performs worse than FRCNN [42] when trained and tested on the target dataset, it performs better than FRCNN [42] when it is evaluated on Caltech without any training on Caltech. It is noteworthy that Faster R-CNN [30] outperforms state-of-the-art pedestrian detectors as well in cross dataset evaluation presented in Table 6. We attribute this to the biasness present in the design of current state-of-the-art pedestrian detectors which are tailored for specific datasets and therefore lack generalization ability. Moreover, a significant performance drop for all methods (though ranking is preserved), including our baseline can be seen in Table 6. However, this performance drop is attributed to lack of diversity and density of the Caltech dataset. Caltech dataset has less annotations than CityPersons and number of people per frame is lower than 1 as reported in Table 1.

5.2 Pre-Training on Autonomous Driving Datasets

As illustrated in Section 5.1, cross dataset evaluation provides insights on the generalization abilities of different benchmarks. A diverse dataset should capture the true essence of real world without bias [4], detector trained on such dataset should be able to learn a generic representation that should handle subtle shifts in domain robustly. Therefore, we use the largest dataset in terms of diversity (more countries and cities included) and pedestrian density from the context of autonomous driving, ECP [4] for training. We performed experiments using our
Table 7: Cross dataset evaluation of our baseline on Autonomous driving benchmarks.

| Training  | Testing   | Reasonable | Small | Heavy |
|-----------|-----------|------------|-------|-------|
| CityPersons | CityPersons | 11.2 | 14.0 | 37.0 |
| ECP       | CityPersons | 11.6 | 12.6 | 39.8 |
| Caltech   | CityPersons | 43.2 | 54.5 | 78.3 |
| ECP       | ECP       | 6.9  | 12.6 | 33.1 |
| CityPersons | ECP       | 17.4 | 40.5 | 49.3 |
| Caltech   | ECP       | 43.2 | 33.7 | 78.3 |
| Caltech   | Caltech   | 6.2  | 7.4  | 58.5 |
| CityPersons | Caltech   | 8.8  | 9.8  | 28.8 |
| ECP       | Caltech   | 8.06 | 9.6  | 29.9 |

Table 8: Benchmarking with CrowdHuman and Wider Pedestrian dataset.

| Training     | Testing  | Reasonable | Small | Heavy |
|--------------|----------|------------|-------|-------|
| CrowdHuman   | Caltech  | 3.4        | 11.2  | 32.3  |
| CrowdHuman   | CityPersons | 15.1 | 21.4 | 49.8 |
| CrowdHuman   | ECP      | 17.9       | 36.5  | 56.9  |
| Wider Pedestrian | Caltech   | 3.2        | 10.8  | 31.7  |
| Wider Pedestrian | CityPersons | 16.0 | 21.6 | 57.4 |
| Wider Pedestrian | ECP      | 16.1       | 32.8  | 58.0  |

baseline, since it has shown to be most robust to domain shifts. Intuitively, from Table 7 it is evident that the best performances are achieved by training and testing on the target dataset. However, in the case of testing on CityPersons, it can be observed that a trained model on ECP performs on par with the model trained on CityPersons. It is because of two reasons A) CityPersons and ECP are recorded from similar cameras and visually it’s not easy to distinguish between images of these two datasets. B) ECP contains roughly 10 times more pedestrians than CityPersons (c.f. Table 1), therefore, it is a better source for learning a robust representation. This claim can be further validated by the fact that opposite is not true, model trained on CityPersons does not perform comparably with the model trained on ECP as shown in Table 7 since CityPersons contains fewer instances of pedestrians than ECP, model was not able to learn a robust representation. Finally, in the case of Caltech, we can see that pre-training on CityPersons and ECP is generally beneficial. Simple pre-training helps to achieve performances comparable to the model trained on the Caltech, primarily due to relative high density and diversity of ECP and CityPersons than Caltech.

5.3 Pre-Training on Diverse Pedestrian Datasets

Table 8 presents results of pre-training of our baseline on CrowdHuman and Wider Pedestrian datasets, respectively. These two datasets are different from autonomous driving datasets as they contain web-crawled images of
Table 9: Investigating the effect on performance when CrowdHuman, Wider Pedestrian and ECP are merged and our baseline is trained only on the merged dataset.

| Training                                      | Testing | Reasonable | Small | Heavy |
|-----------------------------------------------|---------|------------|-------|-------|
| Wider Pedestrian + CrowdHuman + ECP           | CP      | 10.9       | 12.7  | 43.1  |
| Wider Pedestrian + CrowdHuman \rightarrow ECP | CP      | 9.7        | 12.1  | 39.8  |
| CrowdHuman \rightarrow ECP                   | CP      | 10.3       | 12.6  | 40.7  |
| Wider Pedestrian \rightarrow ECP             | CP      | 9.7        | 11.8  | 37.7  |

persons in different scenarios (not just street view images, making them both diverse and dense). Since the autonomous driving datasets (Caltech [12], CityPersons [42] and ECP [4]) lack in density and diversity [1], CrowdHuman [31] and Wider Pedestrian [1] are a suitable choice for pre-training, since average person per frame and crowd density is much larger than that of autonomous driving datasets. In Table 8, it can be observed that mere pre-training on CrowdHuman [31] and Wider Pedestrian [1] can reduce nearly half of the error on Caltech dataset, outperforming previous state-of-the-art, that are trained only on Caltech. We also investigated concatenating all datasets (Table 9), this leads to slight improvement in performance but it is still slightly worse than the progressive training that we have used, where we fine-tune on the autonomous driving benchmark. The results illustrate that this strategy enables us to significantly surpass the performances of state-of-the-art without fine-tuning on the actual target set. This illustrates the generalization capability of the proposed progressive training strategy, without exposure to the target set, our baseline outperforms previous state-of-the-art on CityPersons.

6 Discussion and Analysis

6.1 Effect of Fine-tuning on Target Data

With study presented in section 5, we find that existing methods may overfit on a single dataset, and so we suggest to put more emphasis on cross-dataset evaluation for a new way of benchmarking. However, to align to the previously established evaluation protocol on single dataset and compare to the existing state of the art, we conduct an additional study on fine-tuning our above models on target data. Experimental results show that, with progressively trained and generalizable baseline models, it is relatively more easy to adapt to new datasets by fine-tuning, and further performance gain can be achieved.

Therefore, we investigated the effect of pre-training on a large scale autonomous driving dataset along with fine-tuning on target dataset as reported in Table 10. $A \rightarrow B$ refers to pre-training on $A$ and fine-tuning on the target dataset $B$. Visible improvements can be seen in the case of Caltech [12], which resonates with our previous findings that due to low-resolution and sparse annotation, pre-training on ECP or CityPersons [12] boosts the performances on Caltech [12].
Table 10: Showing how well CityPersons (CP) and ECP are as the source of pre-training.

| Training       | Reasonable | Small | Heavy |
|----------------|------------|-------|-------|
| CP → Caltech   | 5.9        | 8.6   | 27.0  |
| ECP → Caltech  | 5.7        | 7.7   | 26.8  |
| CP → ECP       | 6.8        | 12.3  | 33.0  |
| ECP → CP       | 9.59       | 11.04 | 36.0  |

Importantly, in the case of CityPersons [42], the pre-training on ECP brings improvement of nearly 2% of $MR^{-2}$, as discussed above, ECP brings density, both in terms of number of pedestrians and pedestrians per frame. Conversely, due to relative smaller size, the pre-training on CityPersons [42] does not bring any improvements on ECP.

On much challenging autonomous driving datasets such as CityPersons [42] and ECP [4] as shown in Table 8, mere pre-training on diverse and dense pedestrian datasets does not result in any improvements compared to second and fifth row of Table 7. Since CrowdHuman [31] and Wider Pedestrian [1] though larger in diversity and density still are relatively under-represented in terms of only autonomous driving scenes, therefore fine-tuning on the target dataset is a necessity. In Table 11, we present results of pre-training on a dataset and fine-tuning on the target dataset. $A \rightarrow B$ refers to pre-training on $A$ and fine-tuning on the target dataset $B$. Table 11 shows that pre-training on a web-crawled dataset, with large diversity and density and subsequently fine-tuned on the target dataset provides significant improvements over only pre-training on the autonomous driving datasets and fine-tuning on the target datasets. Improvements are consistent across all datasets and on all occlusion and size settings. In comparison with Table 10 where pre-training is done on autonomous driving datasets, improvement across all dataset (taking the best cases) are 3.3%, 0.4% and 2.4% of $MR^{-2}$ percentage points on Caltech, CityPersons [42] and ECP [4], respectively. Interestingly, Wider Pedestrian [1] appears to be slightly better source of pre-training than CrowdHuman [31] since it contains more images of autonomous driving scenes. Finally, in Table 12 starting with a pre-training on the web-crawled dataset, we fine-tuned our model on the largest autonomous driving dataset ECP [4] and subsequently fine-tuning on the target dataset. We refer to this as our *progressive training pipeline*, results show that the best performances are achieved by using this training pipeline. Significant improvements across all datasets and under all evaluation settings can be observed using the progressive training pipeline where we eventually fine-tune on the target domain. Particularly, in comparison with Table 11 progressive pipeline improves upon previous performances on reasonable/heavy subsets of CityPersons dataset by 1.6%/14.4% and on Caltech by 0.7%/5.0% in terms of log average miss rate ($MR^{-2}$) points.

Note that though fine-tuning to a very specific domain does improve the performance on that domain, it requires human effort to annotate more data.
Table 11: Illustrating how our baseline behave with fine-tuning on the target dataset when CrowdHuman and Wider Pedestrian are used as a source of pre-training.

| Training                  | Reasonable | Small | Heavy |
|---------------------------|------------|-------|-------|
| CrowdHuman→Caltech        | 2.7        | 10.9  | 31.0  |
| Wider Pedestrian→Caltech  | **2.4**    | **9.8** | **30.7** |
| CrowdHuman→CP             | 9.2        | 14.7  | 38.02 |
| Wider Pedestrian→CP       | **9.1**    | **11.0** | **34.4** |
| CrowdHuman→ECP            | 4.5        | 9.3   | 23.0  |
| Wider Pedestrian→ECP      | **4.4**    | **9.1** | **21.3** |

Table 12: Showing the effect of fine-tuning in a cascaded manner.

| Training                  | Reasonable | Small | Heavy |
|---------------------------|------------|-------|-------|
| ECP→Caltech               | 5.7        | 7.7   | 26.8  |
| CrowdHuman→ECP→Caltech    | 2.2        | 8.1   | 30.7  |
| Wider Pedestrian→ECP→Caltech | 1.7       | **7.2** | **25.7** |
| ECP→CP                    | 9.5        | 11.0  | 36.0  |
| CrowdHuman→ECP→CP         | 8.0        | 8.5   | 27.0  |
| Wider Pedestrian→ECP→CP   | **7.5**    | **8.0** | **28.0** |

from that domain, and the obtained model may only be useful on that domain but no longer be generally effective on other domains. Therefore, to avoid human annotation in deployment of the detector and to keep a general model that can be applied to most scenarios, we still prefer to train a universal model and validate it by cross-dataset evaluation without adaptation on target data.

6.2 Comparison with Current State-of-the-Art

In this section we present a comparative analysis of state-of-the-art of pedestrian detection. For our comparative analysis, we choose the best performing pedestrian detectors on Caltech [12] and CityPersons [42]. The underlying goal is to illustrate how well our baseline performs when it is fine-tune on the target dataset. We refer to the best performing baseline presented in Table 12 as Cascade R-CNN†. Table 13 shows that Cascade R-CNN† achieves 1.76 MR−2 on Caltech [12], outperforming previous best by a margin of 3.24% of MR−2. This performance is approaching human-baseline (0.88) [41] on Caltech [12]. Moreover, we report similar improvement over the previous state-of-the-art on CityPersons [42] benchmark. Cascade R-CNN’s† performance is 3.5% MR−2 better than CSP [23]. Finally, on ECP [4] we report an improvements of 1.8% MR−2 over Faster R-CNN [30]. Similar performance improvements are achieved on other subsets of all these three datasets, with the performance improvement of more than 50% for the most challenging subsets, Heavy and small. This con-
Table 13: Comparison with state-of-the-art on Caltech.

| Method         | Reasonable | Heavy | All |
|----------------|------------|-------|-----|
| DeepParts [34] | 11.89      | 60.42 | –   |
| CompactACT-Deep [7] | 9.2       | –     | –   |
| FRCNN [42]    | 8.7        | 53.1  | 62.6|
| RPN + BF [40] | 7.3        | 54.6  | 59.9|
| ALFNet [22]   | 6.1        | 51.0  | 59.1|
| Hyper Learner [25] | 5.5      | 48.7  | 61.5|
| Rep Loss [37] | 5.0        | 47.9  | 59.0|
| CSP [23]       | 5.8        | 46.6  | 57.7|
| Cascade R-CNN † | 1.7        | 25.7  | 27.4|

Persistent improvement over all datasets illustrates the robustness of the Cascade R-CNN †, as it significantly outperform previous state-of-the-art.

Table 14: Comparison with state-of-the-art on ECP. The results are evaluated on the testing set.

| Method         | Reasonable | Small | Heavy |
|----------------|------------|-------|-------|
| Faster R-CNN   | 7.3        | 16.6  | 52.0  |
| YOLOv3         | 8.5        | 17.8  | 37.0  |
| SSD            | 10.5       | 20.5  | 42.0  |
| Cascade R-CNN † | 5.5        | 11.7  | 26.1  |

6.3 Application Oriented Models

In many pedestrian detection applications, the size and computational cost of models is constrained. We experiment with a small and light-weight model MobileNet [18], which is designed for mobile and embedded vision applications, to investigate if the performance improvements hold true. Table 16 shows results on CityPersons [42] using MobileNet [18] as a backbone network architecture into our baseline. Intuitively, MobileNet [18] performs worse than the HRNet [36]. However, in the case of MobileNet [18] as well, we see pre-training on CrowdHuman [31] and fine-tuning on CityPersons [42] improves the performance of the MobileNet [18]. Subsequently, we pre-train (3rd row) MobileNet [18] on CrowdHuman [31] and ECP [4] before fine-tuning on CityPersons [42]. Improvement of nearly 1% of MR<sup>-2</sup> can be observed. Furthermore, we replaced CrowdHuman [31] with Wider Pedestrian [1] as the initial source of pre-training. Improvement over the baseline (1st row) can be observed (4th row). Importantly, in the last row of Table 16, largest gain can be observed. This is consistent with our previous finding reported in Table 12, Wider Pedestrian [1] is a better source of pre-training than CrowdHuman [31], since it has images of autonomous
Table 15: Comparison with state-of-the-art on CityPersons.

| Method           | Backbone       | Reasonable | Heavy | Partial Bare | Small | Medium | Large | Test Time |
|------------------|----------------|------------|-------|--------------|-------|--------|-------|-----------|
| FRCNN [42]       | VGG-16         | 15.4       | -     | -            | 25.6  | 7.2    | 7.9   | -         |
| RetinaNet [20]   | ResNet-50      | 15.6       | 49.9  | -            | -     | -      | -     | -         |
| CornerNet [19]   | Hourglass-54   | 21.0       | 56.0  | -            | -     | -      | -     | -         |
| FRCNN+Seg [42]   | VGG-16         | 14.8       | -     | -            | 22.6  | 6.7    | 8.0   | -         |
| CornerNet        | Hourglass-54   | 21.0       | 56.0  | -            | -     | -      | -     | -         |
| OR-CNN [43]      | VGG-16         | 12.8       | 55.7  | 15.3         | 6.7   | -      | -     | -         |
| RepLoss [37]     | ResNet-50      | 13.2       | 50.9  | 16.8         | 7.6   | -      | -     | -         |
| TLL [32]         | ResNet-50      | 15.5       | 53.6  | 17.2         | 10.0  | -      | -     | -         |
| TLL+MRF [43]     | ResNet-50      | 14.4       | 52.0  | 15.9         | 9.2   | -      | -     | -         |
| ALFNet [22]      | ResNet-50      | 12.0       | 51.9  | 11.4         | 8.4   | 19.0   | 5.7   | 6.6       |
| CSP [23]         | ResNet-50      | 11.0       | 49.3  | 10.4         | 7.3   | 16.0   | 3.7   | 6.5       |
| **Cascade R-CNN** | **HRNet**     | **7.5**    | **33.9** | **5.7** | **6.2** | **8.0** | **3.0** | **4.3** |

Table 16: Investigating the performance of embedded vision model, when pre-trained on diverse and dense datasets.

| Training                | Reasonable | Small | Heavy |
|-------------------------|------------|-------|-------|
| CP                      | 12.0       | 15.3  | 47.8  |
| CrowdHuman→CP           | 11.8       | 14.6  | 41.6  |
| CrowdHuman→ECP→CP       | 10.9       | 14.4  | 44.6  |
| Wider Pedestrian→CP     | 11.7       | 14.9  | 45.6  |
| Wider Pedestrian→ECP→CP | **10.1**   | **11.9** | **35.4** |

driving scenes as well making it more diverse than CrowdHuman [31]. Interestingly, in the case of CrowdHuman [31] and Wider Pedestrian [1], even with a light-weight architecture, our baseline outperformed state-of-the-art pedestrian detector CSP [23]. In summary, even with a light weight back-bone architecture, by pre-training on diverse and dense datasets, MobileNet [18] outperformed previous best performing method on CityPersons [42], i.e. CSP [23].

7 Conclusions

Encouraged by the recent progress of pedestrian detectors on existing benchmarks from the context of autonomous driving, we assessed real world performance of several state-of-the-art pedestrian detectors using standard cross dataset evaluation. We came to the conclusion that current state-of-the-art detectors despite achieving impressive performances on several benchmarks, poorly handle even small domain shifts. This is due to the fact that the current state-of-the-art pedestrian detectors are tailored for target datasets and their overall design contains biasness towards target datasets, thus reducing their generalization. In contrast, general object detectors are more robust and generalize better to new datasets. Moreover, current popular autonomous driving benchmarks lack in crowd-density and more importantly diversity. Simply increasing scale without diversity, results only in a limited gain in performance. Web-crawled
diverse pedestrian datasets provide a rich source for learning a more robust representation for pedestrians. Since web-crawled pedestrian datasets contain more person per image, they are likely to contain more human poses, different sizes and occlusion scenarios; enabling models to learn a more generalize representations. In this work, we have illustrated that pre-training on such diverse and dense datasets and subsequently fine-tuning on the autonomous driving datasets increase the generalization ability of the detectors, makes them more robust to occlusion and provides significant performance improvement which are in some cases within striking distance of a human-baseline.

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