Point in, Box out: Beyond Counting Persons in Crowds
Yuting Liu, Miaojing Shi, Qijun Zhao, Xiaofang Wang

To cite this version:
Yuting Liu, Miaojing Shi, Qijun Zhao, Xiaofang Wang. Point in, Box out: Beyond Counting Persons in Crowds. CVPR 2019 - IEEE Computer Vision and Pattern Recognition Conference, Jun 2019, Long Beach, United States. pp.1-10. hal-02383057

HAL Id: hal-02383057
https://inria.hal.science/hal-02383057
Submitted on 27 Nov 2019

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L’archive ouverte pluridisciplinaire HAL, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d’enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.
Point in, Box out: Beyond Counting Persons in Crowds

Yuting Liu\textsuperscript{1}, Miaojing Shi\textsuperscript{2}, Qijun Zhao\textsuperscript{1}, Xiaofang Wang\textsuperscript{2}

\textsuperscript{1}College of Computer Science, Sichuan University
\textsuperscript{2}Univ Rennes, Inria, CNRS, IRISA

yuting.liu@stu.scu.edu.cn; miaojing.shi@inria.fr; qjzhao@scu.edu.cn

Abstract

Modern crowd counting methods usually employ deep neural networks (DNN) to estimate crowd counts via density regression. Despite their significant improvements, the regression-based methods are incapable of providing the detection of individuals in crowds. The detection-based methods, on the other hand, have not been largely explored in recent trends of crowd counting due to the needs for expensive bounding box annotations. In this work, we instead propose a new deep detection network with only point supervision required. It can simultaneously detect the size and location of human heads and count them in crowds. We first mine useful person size information from point-level annotations and initialize the pseudo ground truth bounding boxes. An online updating scheme is introduced to refine the pseudo ground truth during training; while a locally-constrained regression loss is designed to provide additional constraints on the size of the predicted boxes in a local neighborhood. In the end, we propose a curriculum learning strategy to train the network from images of relatively accurate and easy pseudo ground truth first. Extensive experiments are conducted in both detection and counting tasks on several standard benchmarks, e.g. ShanghaiTech, UCF\textsubscript{CC}\textsubscript{50}, WiderFace, and TRANCOS datasets, and the results show the superiority of our method over the state-of-the-art.

1. Introduction

Counting people in crowded scenes is a crucial component for a wide range of applications including video surveillance, safety monitoring, and behavior modeling. It is a highly challenging task in dense crowds due to heavy occlusions, perspective distortions, scale variations and varying density of people. Modern regression-based methods \[27, 49, 41, 25, 22, 20, 39\] cast the problem as regressing a density distribution map whose integral over the map gives the people count within that image (see Fig 1: Left). Owing to the advent of deep neural networks (DNN) \[17\], remarkable progress has been achieved in these methods. They do not require annotating the bounding boxes but only the points of person heads at training. Yet, as a consequence, they can not provide the detection of persons at testing, neither.

The detection-based methods, which cast the problem as detecting each individual in the crowds (see Fig 1: Right), on the other hand, have not been largely explored in recent trends due to the lack of bounding box annotations. Liu et al. \[22\] have tried to manually annotate on partial of the bounding boxes in ShanghaiTech PartB (SHB) dataset \[49\] and train a fully-supervised Faster R-CNN \[32\]. They combine the detection result with regression result for crowd counting. Notwithstanding their efforts and obtained improvements, they did not report results on datasets like SHA \[49\] and UCF\textsubscript{CC}\textsubscript{50} \[13\], which have crowds on average five and ten times denser than that of SHB.

Annotating the bounding boxes of persons for training images can be a great challenge in crowd counting datasets. Meanwhile, knowing the person size and locations in a crowd at test stage is also very important; for example, in video surveillance, it enables person recognition \[37\], tracking \[33\], and re-identification \[21\]. Recently, some researchers \[18, 14\] start to work on this issue with point su-
pervision by employing segmentation frameworks [18] or regressing the localization maps [14] to simultaneously localize the persons and predict the crowd counts. Because they only use point-level annotations, they simply focus on localizing persons in the crowds, but do not consider predicting the proper size.

To be able to predict the proper size and locations of persons and meanwhile bypass the need for expensive bounding box annotations, we introduce a new deep detection network using only point-level annotations on person heads (see Fig. 1: Middle). Although the real head size is not annotated, the intuition of our work is based on the observations that i) when two persons are close enough, their head distance indeed reflects their head size (similar to [49]); ii) due to the perspective distortion, person heads in the same horizontal line usually have similar size and gradually become smaller in the remote (top) area of the image. Both observations are common in crowd counting scenarios. They inspire us to mine useful person size information from head distances, and generalize a reliable point-supervised person detector with the help of head point annotations and size correlations in local areas.

To summarize, our work tries to tackle a very challenging yet meaningful task which is never handled by before; we propose a point-supervised deep detection network (PS-DDN) for crowd counting which takes in cheap point-level annotations on person heads at training stage and produces out elaborate bounding box information on person heads at test stage. The contribution is three-fold:

- We propose a novel online pseudo ground truth updating scheme which initializes the pseudo ground truth bounding boxes from point-level annotations (Fig. 1: Middle top) and iteratively updates them during training (Fig. 1: Middle bottom). The initialization is based on the nearest neighbor head distances.
- We introduce a novel locally-constrained regression loss in the point-supervised setting which encourages the predicted boxes in a local band area to have the similar size. The loss function is inspired from the perspective distortion impact on the person size in an image [39, 6, 47];
- We propose a curriculum learning strategy [3] to feed the network with training images of relatively accurate and easy pseudo ground truth first. The image difficulty is defined over the distribution of the nearest neighbor head distances within each image.

In extensive experiments, we show that (1) PSDDN performs close to those regression-based methods in crowd counting task on ShanghaiTech and UCF_CC_50 datasets; outperforms the state-of-the-arts by integrating with them. (2) In the mean time it produces very competitive results in person detection task on ShanghaiTech, UCF_CC_50, and WiderFace [46] datasets. (3) We also evaluate PSDDN on the vehicle counting dataset TRANCOS [10] to show its generalizability in other detection and counting tasks.

2. Related works

We present a survey of related works in three aspects: (1) detection-based crowd counting; (2) regression-based crowd counting; and (3) point-supervision.

2.1. Detection-based crowd counting

Traditional detection-based methods often employ motion and appearance cues in video surveillance to detect each individual in a crowd [43, 5, 29]. They are suffered from heavy occlusions among people. Recent methods in the deep fashion learn person detectors relying on exhaustive bounding box annotations in the training images [42, 22]. For instance, [22] have manually annotated the bounding boxes on partial of SHB and trained a Faster R-CNN [32] for crowd counting. The annotation cost can be very expensive and sometimes impractical in very dense crowds. Our work instead uses only the point-level annotations to learn the detection model.

There are some other works particularly focusing on small object detection, e.g. faces [12, 26, 1]. [12] proposed a face detection method based on the proposal network [39] while [26] proposed to detect and localize faces in a single stage detector like SSD [23]. The face crowds tackled in these works are however way less dense than those in crowd counting works; moreover, these works are typically trained with bounding box annotations.

2.2. Regression-based crowd counting

Earlier regression-based methods regress a scalar value (people count) of a crowd [6, 7, 13]. Recent methods instead regress a density map of a crowd; crowd count is obtained by integrating over the density map. Due to the use of strong DNN features, remarkable progress has been achieved in recent methods [49, 35, 41, 25, 22, 24, 31, 14, 39]. More specifically, [41] designed a contextual pyramid DNN system. It consists of both a local and global context estimator to perform patch-based density estimation. [24] leveraged additional unlabeled data from Google Images to learn a multi-task framework combining both counting information in the labeled data and ranking information in the unlabeled data. [31] proposed an iterative crowd counting network which first produces the low-resolution density map and then uses it to further generate the high-resolution density map. Despite the significant improvements achieved in these regression-based methods, they are usually not capable of predicting the exact person location and size in the crowds.

[22, 18, 14] are three most similar works to ours. [22] designed a so-called DecideNet to estimate the crowd density by generating detection- and regression-based density
maps separately; the final crowd count is obtained with the guidance of an attention module. [14] introduced a new composition loss to regress both the density and localization maps together, such that each head center can be directly inferred from the localization map. [18] employed the hourglass segmentation network [34] to segment the object blobs in each image for crowd counting; instead of using per-pixel segmentation labels, they use only point-level annotations [2]. Our work is similar to [22] in the sense we both train a detection network for crowd counting; while [22] trained a fully-supervised detector using bounding box annotations, we train a weakly-supervised detector using only point-level annotations. Our work is also similar to [14, 18] where we all use point-level annotations; unlike our method, [14, 18] simply focus on person localization whereas we aim to predict both the localization and proper size of the person. Apart from all above, we also notice that we firstly evaluate the detection results on the dense crowd counting datasets i.e. ShanghaiTech and UCF_CC_50.

2.3. Point supervision

Point supervision scheme has been widely used in human pose estimation to annotate key-points of human body parts [16, 30, 36]; while in object detection or segmentation, it has often been employed to reduce the annotation time [4, 44, 45, 2, 28]. For example, Bearman et al. [2] conducted semantic segmentation by asking the annotators to click anywhere on a target object while Papadopoulos et al. [28] asked the annotators to click on the four physical points on the object for efficient object annotations. The points can be collected either once offline [2] or in an online interactive manner [4, 44, 45]. We collect the points once and only use them at training time.

3. Method

3.1. Overview

Our model is based on the widely used anchor based detection framework, such as RPN [32] and SSD [23]. The network architecture is shown in Fig. 2 where we adopt our backbone from ResNet-101 with four ResNet blocks (Res B1- B4) [11]. Likewise in [12], the outputs from Res B3 and Res B4 are taken to connect with two detection layers with different scales of anchors, respectively. The detection layer is a 1 x 1 convolutional layer that has the output of \(N \times N \times T \times (1+4)\), where \(N\) is the output length of feature maps and \(T\) is the anchor set size (25 in our work). The aspect ratios of the predefined anchors are adapted from [32] by referring to the centroid clustering of the nearest neighbor distance between person heads. For each anchor, we predict 4 offsets relative to its coordinates and 1 score for classification. Prediction Pred2 is up-sampled to the same resolution with Pred1 and added together to produce the final map Final Pred. The multi-task loss of bounding box classification and regression is applied in the end.

We extend the framework to point-supervised crowd counting with modules marked in bold in Fig. 2: a novel online ground truth (GT) updating scheme is firstly presented which incorporates initializing pseudo GT bounding boxes from point-level annotations and updating them during training. Afterwards, a locally-constrained regression loss is specifically proposed for bounding box regression with point-supervision. In the end, we introduce a curriculum learning strategy to train our model from images of relatively accurate pseudo ground truth first.

3.2. Online ground truth updating scheme

Pseudo ground truth initialization. To train a detection network, we need to first initialize the ground truth bounding boxes from head point annotations. We follow the inspiration in [49] that the head size is indeed related to the distance between the centers of two neighboring heads in crowded scenes. We use it to estimate the size of a bounding-box \(g\) as the center distance \(d(g, NN_g)\) from this head \(g\) to its nearest neighbor \(NN_g\) (see Fig. 2: red dotted line). This makes a square bounding box; we find the corresponding anchor box that has the closest size to this square box as our initialization. We call the initialized bounding boxes pseudo ground truth. Some examples are shown in Fig. 1: Middle top. The estimations in dense crowds (top) are close to the real ground truth while in sparse crowds (bottom) are often bigger.

Pseudo ground truth updating. To train the detection network, we select positive and negative samples from the predefined anchors through their IoU (intersection-over-union) with the initialized pseudo ground truth. A binary classifier is trained over the selected positives and negatives so as to score each anchor proposal. Because the pseudo ground truth initialization is not accurate, we propose to iteratively update them to train a reliable object detector (see Fig. 1). More formally, let \(g^0\) denote an initialized ground truth bounding box at certain position of an image at epoch 0. Over the positive samples of \(g^0\), we select the highest scored one among those whose size (the smaller value of width or height) are smaller than \(d(g, NN_g)\) to replace \(g^0\) in the next epoch; i.e. we denote it by \(g^1\) at epoch 1. The anchor set is densely applied on each detection layer, which guarantees that most pseudo ground truth can be updated with suitable predictions iteratively; if sometimes \(g\) is too small to have positives, it will be simply ignored during training.

We notice that the classification loss we use is the same with [8, 32]. Following [9, 40], we also apply the same online hard mining strategy regarding the positive and negative selections. Below we introduce our locally-constrained regression loss.
3.3. Locally-constrained regression loss

We first refer to [9] for some notations in bounding box regression. The anchor bounding box \( a = (ax, ay, aw, ah) \) specifies the pixel coordinates of the center of \( a \) together with its width and height in pixels. \( a \)'s corresponding ground truth \( g \) is specified in the same way: \( g = (gx, gy, gw, gh) \). The transformation required from \( a \) to \( g \) is parameterized as four variables \( d_x(a), d_y(a), d_w(a), d_h(a) \). The first two specify a scale-invariant translation of the center of \( a \), while the second two specify log-space translations of the width and height of \( a \). These variables are produced by bounding box regressor; we can use them to transform \( a \) into a predicted ground-truth bounding box \( \hat{g} = (\hat{gx}, \hat{gy}, \hat{gw}, \hat{gh}) \):

\[
\begin{align*}
\hat{gx} &= aw \cdot d_x(a) + ax, \\
\hat{gy} &= ah \cdot d_y(a) + ay, \\
\hat{gw} &= aw \cdot \exp(d_w(a)), \\
\hat{gh} &= ah \cdot \exp(d_h(a))
\end{align*}
\]

The target is to minimize the difference between \( g \) and \( \hat{g} \).

The ground truth \( g \) in our framework is a pseudo ground truth: the center coordinates \( gx, gy \) are accurate but \( gw, gh \) are not. Based on this, we can not employ the original bounding box regression loss but instead we propose a locally-constrained regression loss.

We first define a loss function \( l_{xy} \) regarding the center distance between \( g \) and \( \hat{g} \):

\[
l_{xy} = (gx - \hat{gx})^2 + (gy - \hat{gy})^2.
\]

With respect to the loss function on width and height, it is not realistic to directly compare between \( g \) and \( \hat{g} \). We rely on the observation (Observe) that in a crowd image bounding boxes of persons along the same horizontal line should have similar size. This is due to the commonly occurred perspective distortions in crowd images: perspective values are equal in the same row, and decreased from the bottom to top of the image [6, 47, 39]. As long as the camera is not severely rotated and the ground in the captured scene is mostly flat, the above observation should apply. Hence, we propose to penalize the predicted bounding boxes \( \hat{g} \) if its width and height clearly violate the Observe.

Formally, denoting by \( g_{ij} = (gx_{ij}, gy_{ij}, gw_{ij}, gh_{ij}) \) the pseudo ground truth at position \( ij \) on the feature map, we first compute the mean and standard deviation of the widths (heights) of all the bounding boxes within a narrow band area (row: \( i - 1 : i + 1 \); column: \( 1 : W \)) on the feature map, \( W \) is the feature map width. We use \( G_i \) to denote the set of ground truth head positions within the narrow band related to \( i \). The corresponding statistics are:

\[
\begin{align*}
\mu_{w_i} &= \frac{1}{|G_i|} \sum_{mn \in G_i} gw_{mn}, \\
\sigma_{w_i} &= \sqrt{\frac{1}{|G_i|} \sum_{mn \in G_i} (gw_{mn} - \mu_{w_i})^2},
\end{align*}
\]

where \( |G_i| \) signifies the cardinality of the set. \( \mu_{h_i} \) and \( \sigma_{h_i} \) can be obtained in the same way. We adopt a three-sigma rule: if the predicted bounding box width \( \hat{gw}_{ij} \) is larger than \( \mu_{w_i} + 3\sigma_{w_i} \), or smaller than \( \mu_{w_i} - 3\sigma_{w_i} \), it will be penalized; otherwise not. The loss function \( l_{w_{ij}} \) regarding the width of bounding box \( \hat{g}_{ij} \) is thus defined as:

\[
l_{w_{ij}} = \begin{cases} 
(\hat{gw}_{ij} - (\mu_{w_i} + 3\sigma_{w_i}))^2 & \text{if } \hat{gw}_{ij} > \mu_{w_i} + 3\sigma_{w_i} \\
(\hat{gw}_{ij} - (\mu_{w_i} - 3\sigma_{w_i}))^2 & \text{if } \hat{gw}_{ij} < \mu_{w_i} - 3\sigma_{w_i} \\
0 & \text{otherwise}
\end{cases}
\]

The same applies to the loss function on the height.

Figure 2: Network overview of PSDDN using only point-level annotations. Res B1 - B4 denotes the ResNet block adopted from ResNet-101 [11]. Person detection is conducted on two scales after Res B3 and B4; their predictions (Pred1 and Pred2) are summed up to produce the final prediction (Final Pred). We propose an online pseudo ground truth updating scheme which includes pseudo ground truth initialization and updating; a novel locally-constrained regression loss which encourages the predicted boxes in a local area to have the similar size. A curriculum learning strategy is proposed to train the network from images of relatively accurate pseudo ground truth first.
images containing mostly super small/big bounding boxes, the model will already be very good and will do a much better job than training all the samples together from the very beginning. $Z$ is empirically chosen as 3 in our experiment.

4. Experiments

We first introduce two crowd counting datasets and one face detection dataset. A vehicle counting dataset is also introduced to show the generalizability of our method. Afterwards, we evaluate our method on these datasets.

4.1. Datasets

**ShanghaiTech** [49]. It consists of 1,198 annotated images with a total of 330,165 people with head center annotations. This dataset is split into two parts: SHA and SHB. The crowd images are sparser in SHB compared to SHA: the average crowd counts are 123.6 and 501.4, respectively. Following [49], we use 300 images for training and 182 images for testing in SHA; 400 images for training and 316 images for testing in SHB.

**UCF_CC_50** [13]. It has 50 images with 63,974 head center annotations in total. The head counts range between 94 and 4,543 per image. The small dataset size and large variance make it a very challenging counting dataset. We call it UCF for short. Following [13], we perform 5-fold cross validations to report the average test performance.

**WiderFace** [46]. It is one of the most challenging face datasets due to the wide variety of face scales and occlusion. It contains 32,203 images with 393,703 bounding-box annotated faces. The average annotated faces per image are 12.2, 40% of the data are used as training, another 10% form the validation set and the rest are the test set. The validation and test sets are divided into “easy”, “medium”, and “hard” subsets. Test set evaluation has to be conducted by the paper authors. For convenience, we train all models on the train set and evaluate only on the validation set.

**TRANCOS** [10]. It is a public traffic dataset containing 1244 images of different congested traffic scenes captured by surveillance cameras with 46,796 annotated vehicles. The regions of interest (ROI) are provided for evaluation.

4.2. Implementation details

To augment the training set, we randomly re-scale the input image by 0.5X, 1X, 1.5X, and 2X (four scales) and crop 500*500 image region out of the re-scaled output as training samples. Testing is also conducted with four scales of input and combined together. We set the learning rate as $10^{-4}$, with weight decay 0.0005 and momentum 0.9. Given the pseudo ground-truth and anchor bounding boxes during training, we decide positive samples to be those where IoU overlap exceeds 70%, and negative samples to be those where the overlap is below 30%. We use a batch size of

$lh_{ij}$ can be obtained in a similar way. We do not require a strict compliance with the Observe in a local area, but instead design the narrow band and three-sigma rule for the tolerance of head size variation among individuals.

The overall bounding box regression loss $L_{reg}$ is:

$$L_{reg} = \sum_{ij \in G} \tilde{l}x_{ij} + \tilde{l}w_{ij} + \tilde{l}h_{ij}, \tag{5}$$

where $G$ denotes the set of ground truth head points in one image. We add a tilde to each subloss symbol to signify that in real implementation the center coordinates, widths and heights of $g$ and $\hat{g}$ are normalized in a way related to the anchor box $a$ following the Eq. 6-9 in [8].

3.4. Curriculum learning

Referring to Sec. 3.2: in very sparse crowds, the initialized pseudo ground truth are often inaccurate and much bigger than the real ground truth; on the other hand, in very dense crowds, the initializations are often too small and hard to be detected. Both cases are likely to corrupt the model and result in bad detection. Instead of training the model on the entire set once, we adopt a curriculum learning strategy [3, 38, 48] to train the model from images of relatively accurate and easy pseudo ground truth first.

Each pseudo ground truth $g$ is initialized with size $d(g, NN_g)$ (Sec. 3.2). In a typical crowd counting dataset, very big or small boxes are only a small portion, most boxes are of medium/medium-small size, which are relatively more accurate and easier to learn. The mean $\mu$ and standard deviation $\sigma$ of $d(g, NN_g)$ can be computed over the entire training set. We therefore employ a Gaussian function $\Phi(d_g|\mu, \sigma)$ to produce scores for pseudo ground truth bounding boxes, such that the medium-sized boxes are in general assigned with big scores. The mean score within an image is given by $\frac{1}{|G|} \sum_{g \in G} \Phi(d_g|\mu, \sigma)$, where $G$ denotes the bounding box set in the image. We define the training difficulty TL for an image as

$$TL = 1 - \frac{1}{|G|} \sum_{g \in G} \Phi(d_g|\mu, \sigma) \tag{6}$$

If an image contains mostly medium-sized bounding boxes, its difficulty will be small; otherwise, big.

Having the definition of image difficulty, we can split the training set $Z$ into $Z$ folds $Z_1, Z_2, ..., Z_s$ accordingly. Likewise in [38, 48], we start by running PSDDN on the first fold $Z_1$ with images containing mostly medium-sized bounding boxes. Training on this fold will lead to a reasonable detection model. After a couple of epochs running PSDDN on $Z_1$, the process moves on to the second fold $Z_2$, adding all its images into the current working set $Z_1 \cup Z_2$ and running PSDDN again. The process will iteratively move on to the final fold $Z_s$ and run PSDDN on the joint set $Z_1 \cup Z_2 \cup ... \cup Z_s$. By the time it reaches $Z_s$ with

4736

6473
12 images. In general, we train models for 50 epochs and select the best-performing epoch on the validation set.

### 4.3. Evaluation protocol

We evaluate both the person detection and counting performance. For the counting performance, we adopt the commonly used mean absolute error (MAE) and mean square error (MSE) \cite{35, 41, 22} to measure the difference between the counts of ground truth and estimation.

Regarding the detection performance, in the WiderFace dataset, bounding box annotations are available for each face; a good detection \( \hat{g} \) is therefore judged by the IoU overlap between the ground truth \( g \) and detected bounding box \( \hat{g} \), i.e., \( \text{IoU}(g, \hat{g}) > 0.5 \). In the ShanghaiTech and UCF_CC_50 datasets, we do not have the annotations of bounding boxes but only head centers. We define a good detection of \( \hat{g} \) based on two criteria:

- the center distance between the ground truth \( g \) and detected \( \hat{g} \) is smaller than a constant \( c \).
- the width or height of \( \hat{g} \) is smaller than \( r \ast d(g, NN_g) \), where \( r \) is a constant.

\( c \) is set to 20 (pixels) by default. As for \( r \), there does not exist an exact selection of it since the real ground truth bounding boxes are not available. In dense crowds where persons are very close to each other or even occluded, \( r \) could be a bit bigger than 1 to allow a complete detection around each head; while in sparse crowds, it is the opposite that \( r \) should be smaller than 1. Building upon this, we choose \( r \) by default as 0.8 for SHB and 1.2 for SHA and UCF. Different \( c \) and \( r \) will be evaluated in later sessions.

We compute the precision and recall by ranking our detected bounding boxes (good ones) according to their confidence scores. Average precision (AP) is computed eventually over the entire dataset.

### 4.4. Counting

**ShanghaiTech** We first present an ablation study of PSDDN and then compare it with state-of-the-art.

**Ablation study.** We present several variants (Pv0-Pv3) of PSDDN by gradually adding the proposed elements into the network. Referring to Sec. 3, we denote by Pv0 the model trained in a fully-supervised way using the fixed pseudo ground truth initialization and classic bounding-box regression as in \cite{32}; Pv1: the pseudo ground truth in Pv0 is iteratively updated; Pv2: the classic bounding box regression in Pv1 is upgraded to our new way; Pv3 (PSDDN): the curriculum learning strategy is adopted in Pv2.

The result is presented in Table 1 on both SHA and SHB. We take SHA as an example: the MAE for Pv0 starts from 168.6; it decreases to 104.7 for Pv1 and 89.8 for Pv2, respectively; finally, it reaches the lowest MAE 85.4 for Pv3, which is the full version of PSDDN. In the meantime, the MSE also significantly decreases from 268.3 of Pv0 to 159.2 of Pv3. We notice that the same observation goes with SHB as well. The result shows that each component of PSDDN provides a clear benefit in the overall system.

**Comparison with state-of-the-art.** We compare our work with prior arts \cite{20, 31, 24, 22, 41, 35}. It can be seen that our detection-based method PSDDN already performs close to recent density-based methods. Furthermore, bycomb ing our PSDDN result with \cite{20} using the attention module in \cite{22} we show that the obtained result outperforms the state-of-the-art. For instance, on SHA, PSDDN + \cite{20} produces MAE 65.9 on SHA and 9.1 on SHB. We notice two things: 1) we can obtain better counting results by adjusting the detection confidence scores; on the contrary, we fix it with a high value (0.8) for all datasets to guarantee that the predictions are reliable at every local position; 2) the regression-based methods sometimes produce bad results in some local area of the image, which can not be reflected in the MAE metric; there is another metric called GAME \cite{10} which is able to overcome this limitation. We will discuss later in TRANCOS dataset to show that our detection-based method is much better in the GAME metric. We show some examples of PSDDN in Fig. 3.

The notation “DetNet” for \cite{22} denotes the counting-by-detection result in it, where they annotate on partial of the bounding boxes in SHB and train a fully-supervised Faster R-CNN detector. PSDDN clearly outperforms the DetNet results. But we do not claim that point (weakly)-supervised learning is normally better than fully-supervised learning. Specifically for DetNet, they did not employ any of the data augmentation tricks as in PSDDN. The main limitation for fully-supervised detection methods in crowd counting lies

<table>
<thead>
<tr>
<th>Dataset</th>
<th>SHA</th>
<th>SHB</th>
</tr>
</thead>
<tbody>
<tr>
<td>Measures</td>
<td>MAE</td>
<td>MSE</td>
</tr>
<tr>
<td>Pv0</td>
<td>168.6</td>
<td>268.3</td>
</tr>
<tr>
<td>Pv1</td>
<td>104.7</td>
<td>193.8</td>
</tr>
<tr>
<td>Pv2</td>
<td>89.8</td>
<td>169.5</td>
</tr>
<tr>
<td>Pv3(PSDDN)</td>
<td>85.4</td>
<td>159.2</td>
</tr>
<tr>
<td>PSDDN + \cite{20}</td>
<td>65.9</td>
<td>112.3</td>
</tr>
</tbody>
</table>

Table 1: Crowd counting: ablation study of PSDDN (Pv0-Pv3 denote different variants of PSDDN) and its comparison with state-of-the-art on ShanghaiTech dataset.
Figure 3: Examples from WiderFace, SHB, UCF, SHA, and TRANCOS datasets. The top row is test images with ground truth (bounding boxes or dots) while the bottom row is our detection. The numbers in images denote the ground truth and estimated counts, respectively. The green bounding boxes denote good detection while the yellows are not according to our evaluation protocol.

<table>
<thead>
<tr>
<th>Counting Measures</th>
<th>UCF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Li et al. [20]</td>
<td>266.1 397.5</td>
</tr>
<tr>
<td>Liu et al. [24]</td>
<td>279.6 388.9</td>
</tr>
<tr>
<td>Sindagi et al. [31]</td>
<td>295.8 320.9</td>
</tr>
<tr>
<td>Sam et al. [35]</td>
<td>318.1 439.2</td>
</tr>
<tr>
<td>PSDDN</td>
<td>359.4 514.8</td>
</tr>
</tbody>
</table>

Table 2: Comparison of PSDDN with state-of-the-art on UCF dataset. MAE, MSE are reported for crowd counting while AP is reported for person detection.

UCF_CC_50 It has the densest crowds so far in crowd counting task. We show in Table 2 that our PSDDN can still produce competitive result: the MAE is 359.4 while the MSE is 514.8. In the detection session, we will show that despite the tiny heads in UCF, PSDDN is still able to produce reasonable bounding boxes on them (Fig. 3: third column).

4.5. Detection

ShanghaiTech In Fig. 4, we first present the precision-recall curves of different $c$ and $r$ (see Sec. 4.3) on SHA and SHB. The recall rates of different curves stop at some points as we fix the confidence score in the detection output. When we fix $r$, the AP improves with an increase of $c$; $c$ is chosen by default as 20 to apply a hard constraint on the center distance between the prediction and ground truth. On the other hand, when we fix $c$, the AP improves with an increase of $r$. As mentioned in Sec. 4.3, the crowds in SHA are much denser than in SHB, we choose by default $r = 1.2$ for SHA and $r = 0.8$ for SHB. We also present the result of $r = \infty$ which only cares the head center localizations (like in [18, 14]): we get very good AP 0.737 and 0.759 for SHA and SHB, respectively. [18, 14] did not present localization results in ShanghaiTech, we can not directly compare with them. But simply localizing the head centers is not enough for a detection task, we will further discuss in the WiderFace dataset where we have the real ground truth bounding boxes for evaluation.

Following the counting experiment, we also present the ablation study of PSDDN in detection. The result is shown in Table 3: the AP on SHA is significantly increased from 0.308 for Pv0 to 0.554 for Pv3; the same goes for SHB, where the AP is increased from 0.015 to 0.663 eventually. We notice we also tried to train a Faster R-CNN [32] using the fixed pseudo ground truth, which is as low as in Pv0.

UCF_CC_50 Table 2 shows the detection performance of PSDDN on UCF. In this dataset with very dense crowds, our method still achieves the AP of 0.536. An example is

Table 3: Person detection: ablation study of PSDDN on ShanghaiTech (SHA and SHB) dataset. AP is reported.
shown in Fig. 3; third column. We refer the readers to those people sitting in the upper balcony (e.g. yellow ones): they are not annotated as ground truth but detected by PSDDN.

**WiderFace** WiderFace is a face detection dataset, its crowd density is less denser than that in a typical crowd counting dataset; we report results in Table 4 to show the generalizability of our method. It can be seen using only point-level annotations PSDDN still manages to achieve AP 0.605, 0.605, 0.396 on the easy, medium, and hard set.

**Comparison to others.** Since we have the bounding box annotations available for both training and test in WiderFace, we try to compare PSDDN with [18, 14, 22], [18, 14] predicts either localization maps or segmentation blobs for both object localization and crowd counting. Predicting the exact size and shape of the object is not considered necessary for crowd counting in their works. However, we argue that it is important to object recognition and tracking. We assume there exists another method that can correctly localize every head center at test (better than any of [18, 14]), bounding boxes are added in a post-processing way using the mean ground truth size from the training set. It is denoted as Avg.BB in Table 4. The results are very low. We notice that we also tried to add the boxes in a similar way to our pseudo ground truth initialization at each test point, the APs are also very low. This demonstrates that it is not straightforward to add bounding boxes on top of the head point localization results. We also compare PSDDN with Faster R-CNN [32] using two different levels of annotations in Table 4: FR-CNN (ps) and FR-CNN (fs). First, we use the head point annotations together with the mean ground truth size to generate bounding boxes for training; it performs much worse than our PSDDN. Next, we follow [15] to use the manually annotated bounding boxes to train Faster R-CNN, which is analogue to the DetNet in [22]. PSDDN performs lower AP than FR-CNN (fs) on the easy and medium set but higher AP on the hard set. We point out that, many faces are well covered by the detection of PSDDN but not taken as good ones (yellow ones in Fig. 3: first column) only because of their low IoU with the annotated ground truth.
References


[18] Issam H Laradji, Negar Rostamzadeh, Pedro O Pinheiro, David Vázquez, and Mark Schmidt. Where are the blobs: Counting by localization with point supervision. In ECCV, 2018.


[42] Russell Stewart, Mykhaylo Andriluka, and Andrew Y Ng. End-to-end people detection in crowded scenes. In CVPR, 2016. 2


