

# Leveraging Self-Supervision for Cross-Domain Crowd Counting

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## Abstract

State-of-the-art methods for counting people in crowded scenes rely on deep networks to estimate crowd density. While effective, these data-driven approaches rely on large amount of data annotation to achieve good performance, which stops these models from being deployed in emergencies during which data annotation is either too costly or cannot be obtained fast enough.

One popular solution is to use synthetic data for training. Unfortunately, due to domain shift, the resulting models generalize poorly on real imagery. We remedy this shortcoming by training with both synthetic images, along with their associated labels, and unlabeled real images. To this end, we force our network to learn perspective-aware features by training it to recognize upside-down real images from regular ones and incorporate into it the ability to predict its own uncertainty so that it can generate useful pseudo labels for fine-tuning purposes. This yields an algorithm that consistently outperforms state-of-the-art cross-domain crowd counting ones without any extra computation at inference time. Code is publicly available at <https://github.com/weizheliu/Cross-Domain-Crowd-Counting>.

## 1. Introduction

Crowd counting is important for applications such as video surveillance and traffic control. For example during the current COVID-19 pandemic, it has a role to play in monitoring social distancing and slowing down the spread of the disease. Most state-of-the-art approaches rely on regressors to estimate the local crowd density in individual images, which they then proceed to integrate over portions of the images to produce people counts. The regressors typically use Random Forests [37], Gaussian Processes [4], or more recently Deep Networks [3,28,39,44,50,51,59,63,69–71,74,77,79,94,105,106,111], with most state-of-the-art approaches now relying on the latter.

Unfortunately, training such deep networks in a traditional supervised manner requires much ground-truth annotation. This is expensive and time-consuming and has



Figure 1. **Motivation.** (a): **Time, expense, and robustness.** Annotating dense crowd is extremely time-consuming. It can take hours for someone to annotate a single image and the process is error prone. (b) **Accuracy:** For region far away from the camera where people are very small and bunched up, it is almost impossible for human beings to annotate accurately. (c): **Privacy issues.** Real images feature real people and information about them will be exposed to the annotator, which can create ethical concerns. (d): **Solution.** All of these problems can be solved by using synthetic data.

slowed down the deployment of data-driven approaches, as illustrated by Fig. 1. One way around this difficulty is to use synthetic data for training purposes. However there is usually too much domain shift—change in statistical properties—between real and synthetic images for networks trained in this manner to perform well.

In this paper, we remedy this shortcoming by training with both synthetic images, along with their associated labels, and *unlabeled* real images. We force our network to learn perspective-aware features on the real images and build into it the ability to use these features to predict its own uncertainty using a fast variant of the ensemble method [14] to effectively use pseudo labels for fine-tuning. We train it as follows:

1. Initially we use synthetic images, unlabeled real images, and upside-down version of the latter. We train the network not only to give good results on the synthetic images but also to recognize if the real images

are upside-up or upside-down. This simple approach to self-supervision forces the network to learn features that are perspective-aware on the real images.

2. At the end of this first training phase in which we perform *image-wise* self supervision on the real images, our network is semi-trained and the uncertainties attached to the people densities it estimates have meaning. We exploit them to provide *pixel-wise* self-supervision by treating the densities the network is confident about as pseudo labels, that we use as if they were ground-truth labels to re-train the network. We iterate this process until convergence.

Our contribution is therefore a novel approach to self-supervision for cross-domain crowd counting that relies on *stochastic* density maps, that is, maps with uncertainties attached to them, instead of the more traditional *deterministic* density maps. Furthermore, it explicitly leverages a specificity of the crowd counting problem, namely the fact that perspective distortion affects density counts. We will show that it consistently outperforms the state-of-the-art cross-domain crowd counting methods.

## 2. Related Work

Given a single image of a crowded scene, the currently dominant approach to counting people is to train a deep network to regress a people density estimate at every image location. This density is then integrated to deliver an actual count [29, 40, 42, 43, 45, 47, 52, 58, 75, 87, 95, 100, 107, 112]. Most methods work on counting people from individual images [10, 76, 80, 86, 96, 103, 104] while others account for temporal consistency in video sequence [15, 46, 48, 49, 94, 108].

While effective these approaches require a large annotated dataset for training purposes, which is hard to obtain in many real-world scenarios. Unsupervised domain adaptation seek to address this difficulty. We discuss earlier approaches to it, first in a generic context and then for the specific purpose of crowd counting.

**Unsupervised Domain Adaptation.** Unsupervised domain adaptation aims to align the source and target domain feature distributions given annotated data *only* in the source domain. A popular approach is to learn domain-invariant features by adversarial learning [8, 9, 11, 12, 17, 23, 24, 26, 33, 55, 56, 68, 83, 84, 93, 109, 110], which leverages one extra discriminator network to narrow the gap between two different domains. Another way to bridge the domain gap is to define a specific domain shift metric that is then minimized during training [13, 30, 31, 35, 36, 38, 41, 53, 54, 61, 62, 65, 85, 97–99]. Other widely used approaches include generating realistic-looking synthetic images [2, 22, 72, 101, 102], incorporating self-training [7, 19, 73, 78], transferring model weights

between different domains [66, 67], and using domain-specific batch normalization [5]. The method of [82] introduces a self-supervised auxiliary task such as detecting image-rotation in unlabeled target domain images for cross-domain image classification and served as an inspiration to us.

**Crowd Counting.** Most of the techniques described above are intended for classification problems and very few have been demonstrated for crowd counting purposes.

One exception is the method of [18, 90, 91] that trains the deep model on synthetic images and then narrows the domain gap, by using a CycleGAN [113] extension to translate synthetic images to make them look real and then re-train the model on these translated images. A limitation of this work is that the translated images, while more realistic than the original synthetic ones, are still not truly real.

Another exception is the method of [81]. It uses pseudo labels generated by a network trained on synthetic images as though they were ground-truth labels. It relies on Gaussian Processes to estimate the variance of the pseudo labels and to minimize it. However, the uncertainty of these pseudo labels is not estimated or taken into account and the computational requirements can become very large when many synthetic images are used simultaneously.

The method of [20] uses adversarial learning to align features across different domains. However, it relies on extra discriminator networks which are complicated and hard to train. [25, 64, 92] leverage a few target labels to bridge the domain gap, therefore require extra annotation cost.

More recent work [6, 21, 57] advocates bridging the domain gap by leveraging real dataset that collected from another scene. However, unlike synthetic data that can be simply rendered to specifically fit the people distribution in target domain, existing real data often features dramatically different scene structure and people distribution. In practice, adding more real data that from another can even decrease the performance if the domain gap is too large [6]. In our ablation study, we will show that our model trained with synthetic data covering a large range of crowd distributions can outperform one trained with an existing real dataset collected from a different scene.

By contrast to these approaches, ours explicitly takes uncertainty into account and leverages a specificity of the crowd counting problem, namely the fact that perspective distortion matters.

## 3. Approach

We propose a fully unsupervised approach to fine-tuning a network that has been trained on annotated synthetic data, so that it can operate effectively on real data despite a potentially large domain shift. At the heart of our method is a network that estimates people-density at every location while

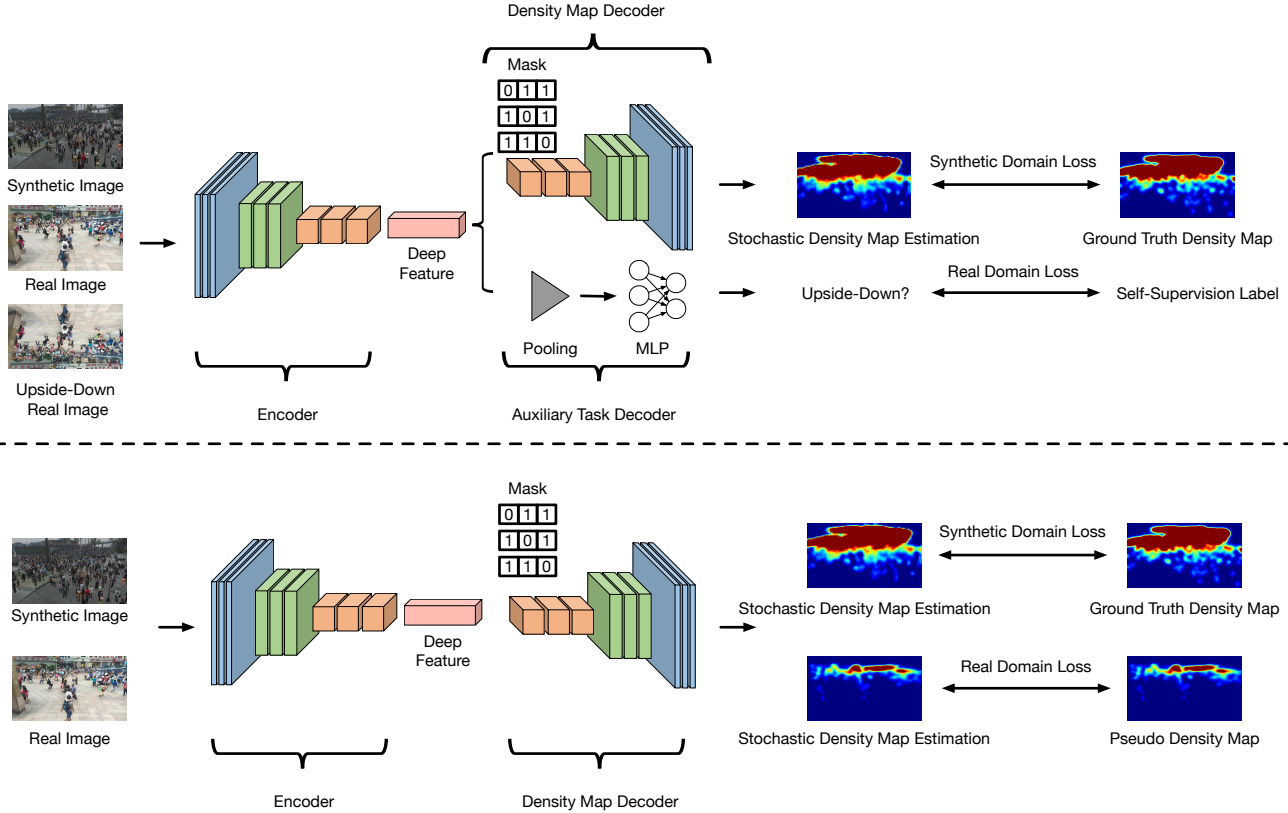


Figure 2. **Two-stage approach.** **Top:** During the first training stage, we use synthetic images, real images, and flipped versions of the latter. The network is trained to output the correct people density for the synthetic images and to classify the real images as being flipped or not. **Bottom:** During the second training stage, we use synthetic and real images. We run the previously trained network on the real images and treat the least uncertain people density estimates as pseudo labels. We then fine tune the network on both kinds of images and iterate the process.

incorporating a variant of the deep ensemble approach [14] to provide uncertainties about these. The key to success is to first pre-train this network so that these uncertainties are meaningful and then to exploit them to recursively fine-tune the network.

We have therefore developed a two-stage approach that first relies on real-images and upside-down versions of these to provide an *image-wise* supervisory signal. We use them to train the network not only to give good results on the synthetic images but also to recognize if the real images are upside-up or upside-down. This yields a partially-trained network that can operate on real images and return meaningful uncertainty values along with the density values. We can therefore exploit them to provide *pixel-wise* supervisory signal, by treating the people density estimates the network is most confident about as pseudo labels, that are treated as ground-truth and use to re-train the network. We iterate this process until the network predictions stabilize. Fig. 2 depicts our complete approach.

### 3.1. Network Architecture

Formally, let  $D^s = \{(\mathbf{x}_i^s, \mathbf{y}_i^s)\}_{i=1}^{N_s}$  be a synthetic source-domain dataset, where  $\mathbf{x}^s$  denotes a color synthetic image and  $\mathbf{y}^s$  the corresponding crowd density map. The target-domain dataset is defined as  $D^t = \{\mathbf{x}_i^t\}_{i=1}^{N_t}$  without ground truth crowd density labels where  $\mathbf{x}^t$  denotes a color real image. In most real-world scenarios, we have  $N_s \gg N_t$ . Our goal is to learn a model that performs well on the target-domain data.

To this end, we use a state-of-the-art encoder/decoder architecture for people density estimation [90]. We chose this one because it has already been used by cross-domain crowd counting approaches and therefore allows for a fair comparison of our approach against earlier ones. Let  $\mathcal{E}$  and  $\mathcal{D}$  be the encoder and decoder networks that jointly form the people density estimation network  $\mathcal{F}$  of [90]. Given an input image  $\mathbf{x}$  as input,  $\mathcal{E}$  returns the deep features  $\mathbf{f} = \mathcal{E}(\mathbf{x})$  that  $\mathcal{D}$  takes as input to return the density map  $\mathcal{D}(\mathbf{f})$ .

One way to enable self-supervision for classification purposes is to use a partially trained network to predict labels

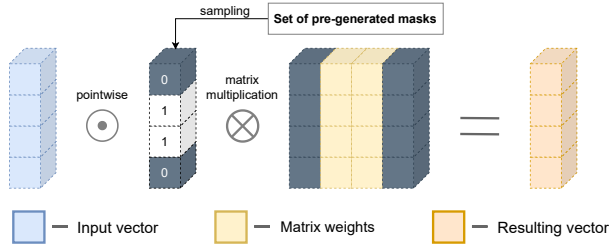


Figure 3. **Masksembles approach.** During training, for every input vector, a binary mask is selected from a set of pre-generated masks and is used to zero out a corresponding set of features. Performing the inference several times using different masks then yields an ensemble-like behavior.

and associated probabilities, treat the most probable ones as *pseudo labels* that can be used for training purposes as though they were ground-truth labels [101, 102]. This strategy is widely used to provide pixel-wise [115] and image-wise [114] self-supervision to address classification problems. If the probability measure is reliable and allows the discarding of potentially erroneous labels, repeating this procedure several times results in the network being progressively refined without any need for ground-truth labels.

To implement a similar mechanism in our context, we need more than labels at the image-level. We require estimates of which individual densities in an estimated density map are likely correct and which are not. In other words, we need a *stochastic* crowd density map instead of the deterministic one that existing methods produce. Among all the methods that can be used to turn our network  $\mathcal{F}$  into one that returns such stochastic density maps, MC-Dropout [16] and Deep Ensembles [34] have emerged as two of the most popular ones. Both of those methods exploit the concept of *ensembles* to produce uncertainty estimates. Deep Ensembles are widely acknowledged to yield significantly more reliable uncertainty estimates [1, 60]. However, they require training many different copies of the network, which can be very slow and memory consuming. Instead, we rely on *Masksembles*, a recent approach [14] that operates on the same basic principle as MC-Dropout. However, instead of achieving randomness by dropping different subsets of weights for each observed sample, it relies on a set of pre-computed binary masks that specify the network parameters to be dropped. Fig. 3 depicts this process.

In practice, we associate to the first convolutional layer of the decoder  $\mathcal{D}$  a Masksembles layer. During training, for each sample in a batch we randomly choose one of the masks, set the corresponding weights to one or zero in the Masksembles layers, which drops the corresponding parts of the model just like standard dropout. During inference, we run the model multiple times, once per mask, to obtain a set of predictions and, ultimately, an uncertainty estimate. This turns out to provide uncertainty estimates that are al-

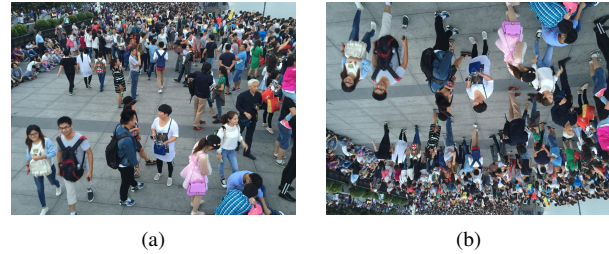


Figure 4. **Upside-up vs Upside-down.** (a) Original image. Due to perspective effects, the apparent size of people is less at the top of the image and the people density appears to be larger. (b) In the upside-down image the effect is reversed. To enable the decoder to distinguish between these two cases, the encoder must produce perspective-aware features, that is, features that take perspective distortion into account and turn out to be important for accurate crowd counting.

most as reliable as those of Ensembles but without having to train multiple networks and is therefore much faster and easier to train. Formally, we write

$$\bar{\mathbf{y}} = \frac{1}{M} \sum_{m=1}^M \mathcal{F}_m(\mathbf{x}), \quad (1)$$

$$\mathbf{u} = \sqrt{\sum_{m=1}^M (\mathcal{F}_m(\mathbf{x}) - \bar{\mathbf{y}})^2}, \quad (2)$$

where  $\mathbf{x}$  is the input image,  $\mathcal{F}_m$  is the modified network  $\mathcal{F}$  used with mask  $m$ .  $\bar{\mathbf{y}}$  and  $\mathbf{u}$  are the same size as input image and we treat the individual values of  $u \in \mathbf{u}$  as pixel-wise uncertainties.

### 3.2. Image-Wise Self-Supervision

$\mathcal{F}_m$  can be trained in a supervised fashion using the synthetic training set  $D^s$  but that does not guarantee that it will work well on real images. Hence, we introduce the auxiliary task decoder  $\mathcal{D}_{aux}$  shown at the top of Fig. 2 whose task is to classify an image as being oriented normally or being upside-down from the features produced by the encoder. To train the resulting two-branch network, we use synthetic images from  $D^s$  along with real images from  $D^t$  and flipped versions of these, such as the ones shown in Fig. 4. For the synthetic images, the output should minimize the usual  $L_2$  loss given the ground-truth density maps and, for the real images, the output should minimize a cross entropy loss for binary classification as being either upside-up or upside-down.

Formally, we introduce the loss function

$$\begin{aligned}
 L_{st1} &= L_s + \lambda_1 L_a, \\
 L_s &= \sum_i \|y_i^s - \mathcal{D}(\mathcal{E}(x_i^s))\|^2, \\
 L_a &= -\sum_i \langle y_i^t, \log(\mathcal{D}_{aux}(\mathcal{E}(x_i^t))) \rangle,
 \end{aligned} \tag{3}$$

which we minimize with respect to the weights of the encoder  $\mathcal{E}$  and the two decoders  $\mathcal{D}$  and  $\mathcal{D}_{aux}$ .  $L_s$  is the  $L_2$  distance between the predicted people density map and the ground truth one  $y_i^s$  while  $L_a$  is the cross-entropy loss for binary classification given the ground-truth upside-up or down label  $y_i^t$  for image  $x_i^t$ . We use this label only for the real images because we have ground truth annotations for the synthetic ones. As will be shown in the results section, this provides sufficient supervision for the synthetic images and also using the image-wise supervision for these brings no obvious improvement.

Note that the  $L_s$  and  $L_a$  use the same encoder  $\mathcal{E}$ . To minimize  $L_a$  and hence correctly estimate if an input image is upside-down or not,  $\mathcal{E}$  must extract meaningful features from the real images and not only from synthetic ones. Furthermore, these features must enable the decoder  $\mathcal{D}$  to handle scene perspective, that is, the fact that people densities are typically higher at the top of the image than the bottom in upside-up images. In other words, minimizing  $L_a$  forces  $\mathcal{E}$  to produce perspective-aware features while minimizing  $L_s$  forces the decoder  $\mathcal{D}$  to operate on such features to properly estimate people densities on the synthetic images. In this way, we make  $\mathcal{E}$  produce features that are appropriate both for synthetic and real images, hence mitigating the domain shift between the two, as will be demonstrated in the results section.

This first training stage is summarized by the first procedure of Alg. 1.

### 3.3. Pixel-Wise Self-Supervision

After the first training stage described above, our model can produce both a density map  $\bar{y}$  and its corresponding uncertainty  $\mathbf{u}$ . Let  $\mathcal{F}_m^0$  be the corresponding network. We can now refine its weights to create increasingly better tuned networks  $\mathcal{F}_m^k$  for  $1 \leq k \leq K$  by iteratively minimizing

$$\begin{aligned}
 L_{st2} &= \sum_i \|y_i^s - \mathcal{F}_m^k(x_i^s)\|^2 \\
 &+ \lambda_2 \sum_i \mathbb{1}_{u_i^{k-1} < u_\alpha} (\bar{y}_i^{k-1} - \mathcal{F}_m^k(x_i^t))^2,
 \end{aligned} \tag{4}$$

where  $\bar{y}_i^{k-1}, \mathbf{u}_i^{k-1} = \mathcal{F}_m^{k-1}(x_i^t)$  and  $\mathbb{1}_{u_i^{k-1} < u_\alpha}$  is one for all densities for which the uncertainty is less than the top  $\alpha\%$  uncertainty  $u_\alpha$ . In other words, at each iteration we use the densities produced by  $\mathcal{F}_m^{k-1}$  for which the uncertainty is low enough as pseudo labels to train  $\mathcal{F}_m^k$ .

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### Algorithm 1 Two-Stage Training Algorithm

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**Require:** Source domain data  $D^s = \{(x_i^s, y_i^s)\}_{i=1}^{N_s}$ .  
**Require:** Unlabeled target domain data  $D^t = \{x_i^t\}_{i=1}^{N_t}$ .

**procedure** FIRST STAGE( $D^s$  and  $D^t$ )

Initialize the weights for people density estimation network  $\mathcal{F}_m$  with single encoder  $\mathcal{E}$  and two decoders  $\mathcal{D}$  and  $\mathcal{D}_{aux}$

**for** # of gradient iterations **do**

Pick one source domain image  $x_i^s$

Pick one target domain image  $x_i^t$

Generating one random variable  $\beta \in [0, 1]$

**if**  $\beta \geq 0.5$  **then**

Flip  $x_i^t$  upside-down

**else**

Do nothing

**end if**

Minimize  $L_{st1}$  of Eq. 3

**end for**

**end procedure**

Generating pseudo labels for  $x_i^t \in D^t$  using  $\mathcal{F}_m$

**procedure** SECOND STAGE( $D^s, D^t$  and pseudo labels for  $x_i^t \in D^t$ )

**for** # of recursive iterations **do**

**for** # of gradient iterations **do**

Pick one source domain image  $x_i^s$

Pick one target domain image  $x_i^t$

Minimize  $L_{st2}$  of Eq. 4

**end for**

Update pseudo labels

**end for**

**end procedure**

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This second training stage is summarized by the second procedure of Alg. 1.

## 4. Experiments

In this section, we first introduce the evaluation metrics and benchmark datasets we use in our experiments. We then provide the implementation details and compare our approach to state-of-the-art methods. Finally, we perform a detailed ablation study.

### 4.1. Evaluation Metrics

Previous works in crowd density estimation use the mean absolute error ( $MAE$ ) and the root mean squared error ( $RMSE$ ) as evaluation metrics [81, 90]. They are defined

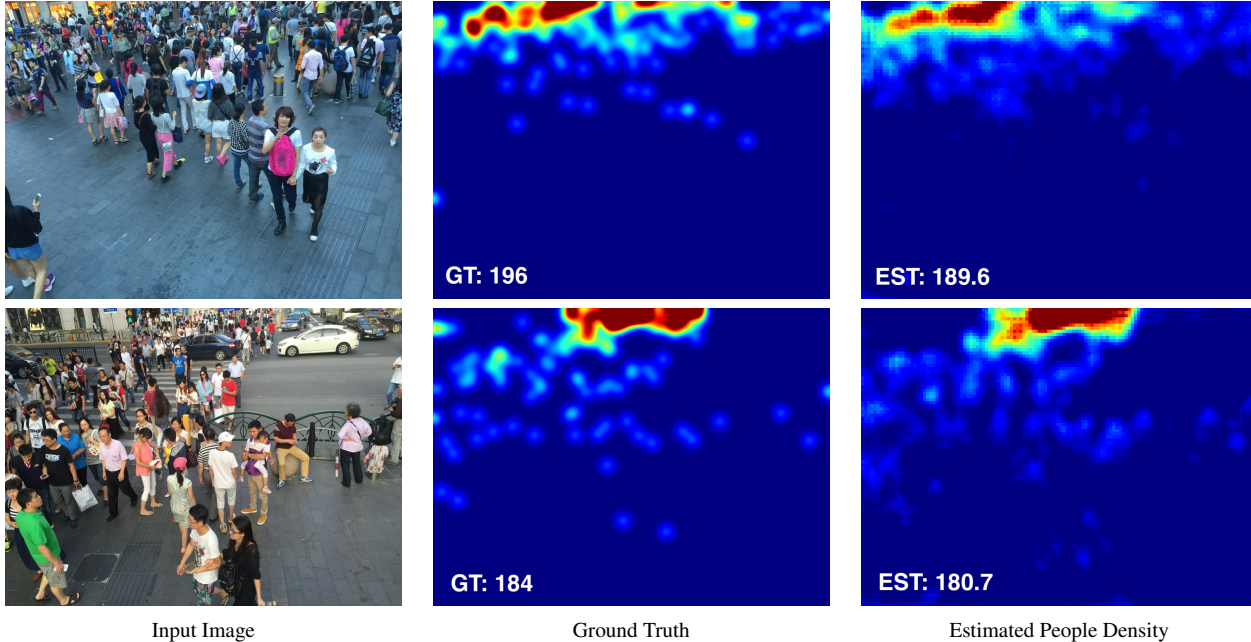


Figure 5. **Density maps.** We indicate the ground-truth and estimated total number of people in the bottom left corner of the density maps. Note how close our estimations are to the ground truth ones. Please refer to the supplementary material for additional such images.

as

$$MAE = \frac{1}{N} \sum_{i=1}^N |z_i - \hat{z}_i| \text{ and } RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (z_i - \hat{z}_i)^2},$$

where  $N$  is the number of test images,  $z_i$  denotes the true number of people inside the ROI of the  $i$ th image and  $\hat{z}_i$  the estimated number of people. In the benchmark datasets discussed below, the ROI is the whole image except when explicitly stated otherwise. The number of people are recovered by integrating over the pixels of the predicted density maps.

## 4.2. Benchmark Datasets

GCC [90] is the synthetic dataset we use. It consists of 15,212 images of size  $1080 \times 1920$ , containing 7,625,843 people annotations. It features 400 different scenes including both indoor and outdoor ones. We test on ShanghaiTech [111], UCF\_CC\_50 [27], UCF\_CC\_50 [27] and WorldExpo'10 [105] and use the same experimental protocols as in earlier work [90]. We briefly describe it in the supplementary material.

## 4.3. Implementation Details

For a fair comparison with previous work [81, 90], we use SFCN [90] as the crowd density regressor and Adam [32] for parameter update with a learning rate of  $1e - 6$ . After a grid search on *one single* dataset as discussed below, we set  $\lambda_1$  in Eq. 3,  $\lambda_2$ , and  $K$  in Eq. 4 to  $10^{-4}$ , 1.0 and 2 respectively for all our experiments.

To estimate uncertainty, we generate 3 stochastic density map for each image and take the standard deviation to be our uncertainty measure. We set the threshold value  $\alpha$  of Eq. 4 to 10, which means that 10% most uncertain pseudo labels are discarded and that we keep the other 90% as pseudo labels for model training. This large percentage is appropriate because there are large areas of the real images that do not contain anyone and for which the pseudo labels are very dependable. We will show below that removing only 10% of the labels suffices to substantially boost performance over keeping all pseudo labels.

Recall that we drop the auxiliary network  $\mathcal{D}_{aux}$  in the second training stage. In the final evaluation phase, we generate only one density map for each image instead of averaging multiple estimates, we will show that the performance is similar for both cases in supplementary material. Hence our model does not require any extra computation at inference time. Fig. 5 depicts qualitative results on ShanghaiTech Part B dataset and we provide additional ones in the supplementary material along with more details about the model.

## 4.4. Comparing against Recent Techniques

In Tab. 1, we compare our results to those of state-of-the-art domain adaptation approaches for each one of the public benchmark datasets, as currently reported in the literature. In each case, we reprint the results as given in these papers and add those of **OURS**, that is, of our method. We consistently and clearly outperform all other methods on all the

Model	MAE	RMSE	Model	MAE	RMSE	Model	MAE	RMSE
No Adapt	160.0	216.5	No Adapt	22.8	30.6	No Adapt	487.2	689.0
Cycle-GAN [113]	143.3	204.3	Cycle-GAN [113]	25.4	39.7	Cycle-GAN [113]	404.6	548.2
SE Cycle-GAN [90]	123.4	193.4	SE Cycle-GAN [90]	19.9	28.3	SE Cycle-GAN [90]	373.4	528.8
SE Cycle-GAN(JT) [88]	119.6	189.1	SE Cycle-GAN(JT) [88]	16.4	25.8	SE Cycle-GAN(JT) [88]	370.2	512.0
SE+FD [20]	129.3	187.6	SE+FD [20]	16.9	24.7	GP [81]	355	505
GP [81]	121	181	GP [81]	12.8	19.2	<b>OURS</b>	<b>336.5</b>	<b>486.1</b>
<b>OURS</b>	<b>109.2</b>	<b>168.1</b>	<b>OURS</b>	<b>11.4</b>	<b>17.3</b>	Supervised	259.3	407.2
Supervised	76.3	144.2	Supervised	11.0	17.1			

Model	MAE	RMSE
No Adapt	275.5	458.5
Cycle-GAN [113]	257.3	400.6
SE Cycle-GAN [90]	230.4	384.5
SE Cycle-GAN(JT) [88]	225.9	385.7
SE+FD [20]	221.2	390.2
GP [81]	210	351
<b>OURS</b>	<b>198.3</b>	<b>332.9</b>
Supervised	134.3	240.3

Model	Scene1	Scene2	Scene3	Scene4	Scene5	Average
No Adapt	4.4	87.2	59.1	51.8	11.7	42.8
Cycle-GAN [113]	4.4	69.6	49.9	29.2	9.0	32.4
SE Cycle-GAN [90]	4.3	59.1	43.7	17.0	7.6	26.3
SE Cycle-GAN(JT) [88]	4.2	49.6	41.3	19.8	7.2	24.4
GP [81]	-	-	-	-	-	20.4
<b>OURS</b>	<b>4.0</b>	<b>31.9</b>	<b>23.5</b>	<b>19.4</b>	<b>4.2</b>	<b>16.6</b>
Supervised	2.7	18.2	14.3	16.1	4.5	11.2

Table 1. **Comparative results on different datasets.** (a) **ShanghaiTech Part A.** (b) **ShanghaiTech Part B.** (c) **UCF\_CC\_50.** (d) **UCF-QNRF.** (e) **WorldExpo’10.** Our approach consistently and clearly outperforms previous state-of-the-art methods on all the datasets.

datasets. And, since we use the same SFCN network architecture as the methods of [81, 90], the performance boost is directly attributable to our approach of domain adaptation.

In Tab. 1, we also compare ourselves to the same model trained in a *fully supervised* fashion on the target domain. Note that our unsupervised approach performs almost as well as the supervised one on Shanghaitech Part B and WorldExpo’10 while there still remains a gap on UCF-QNRF and UCF\_CC\_50. This is because the crowds in Shanghaitech Part B and WorldExpo’10 are still mostly sparse enough for bodies to be visible, just as in the synthetic source domain. By contrast, in UCF-QNRF and UCF\_CC\_50, the crowds are denser and, in many cases, only heads are visible. This creates a larger domain gap between source and target images that could be bridged in future work either by using a synthetic dataset that also features denser crowds or, more ambitiously, by using a detection pipeline that focuses more on heads and would mitigate the domain gap.

#### 4.5. Ablation Study

We perform an ablation study on the UCF-QNRF dataset to highlight the role of the self-supervision loss terms, the impact of stochastic density map, the choice of auxiliary tasks, and the extension of our technique to cross-scene domain adaptation for which the source domain is also real data. In the supplementary material, we provide additional details about hyper-parameter settings and try using other approaches to estimating uncertainty than Masksembles.

**Self-Supervision.** We compare our complete model against several variants. **BASELINE** uses the SFCN crowd

Model	Self-Supervision				MAE	RMSE
	Image	Synthetic Image	Pixel	2nd Image		
<b>BASELINE</b>					275.5	458.5
<b>OURS-IMG</b>	✓				242.8	407.6
<b>OURS-IMG-SYN</b>	✓	✓			243.0	406.8
<b>OURS-PIX</b>			✓		208.3	346.9
<b>OURS</b>	✓		✓		<b>198.3</b>	332.9
<b>OURS-DUP</b>	✓		✓	✓	198.5	<b>331.7</b>

Table 2. **Ablation study on self-supervision.** Both image-wise and pixel-wise self-supervision boost the performance and combining both further improves performance. By contrast, using image-wise self-supervision during the second stage, as opposed to the first, makes no obvious difference.

density estimator trained on the synthetic data and without any domain adaptation. **OURS-IMG** involves the first image-wise training stage but not the second. **OURS-IMG-SYN** also involves only the first image-wise training stage but both real and *synthetic* images can be flipped upside down, whereas in **OURS-IMG** only the real ones are. Conversely, **OURS-PIX** skips the first image-wise training and involves only the second pixel-wise training stage. **OURS-DUP** is similar to our complete approach except for the fact that it uses both pixel-wise and image-wise supervision during the second training stage whereas **OURS** only uses pixel-wise supervision by that point.

As shown in Tab. 2, both **OURS-IMG** and **OURS-PIX** outperform **BASELINE** which shows that both training stages matter. However, **OURS** does even better, which confirms that properly pre-training the network before using pixel-wise supervision matters. Since **OURS-IMG-SYN** and **OURS-DUP** achieve similar performance as **OURS-**

Model	MAE	RMSE
<b>BASELINE</b>	275.5	458.5
<b>BASELINE+Masksembles</b>	<b>273.1</b>	<b>447.9</b>

Table 3. **Ablation study on stochastic density map.** Generating stochastic density map slightly improve the performance but not by a significant amount.

Model	MAE	RMSE
<b>OURS-PIX</b>	208.3	346.9
<b>OURS-MIRROR</b>	208.1	346.0
<b>OURS-90</b>	205.5	344.7
<b>OURS-270</b>	204.8	342.1
<b>OURS</b>	<b>198.3</b>	<b>332.9</b>

Table 4. **Ablation study on auxiliary task.** We tested different auxiliary tasks for image-wise supervision. Flipping the image upside-down yields the best performance and we used it for all other experiments.

**IMG** and **OURS** respectively, we drop image-wise self-supervision for synthetic image and in the second stage for simplicity.

**Stochastic Density Map.** To test if generating a stochastic density map instead of a deterministic one has a significant impact of performance, we compare the performance of **BASELINE** that generates a deterministic map with a version of it that includes Masksembles to generate a stochastic map but still without any domain adaptation. As can be seen in Tab. 3, the version with Masksembles does slightly better but not by a significant amount. Therefore, Masksembles by itself does not account for the large improvements we saw in Tab. 1.

**Choice of Auxiliary Tasks.** Having chosen to use inverted images to provide a self-supervision signal may seem arbitrary during the first phase of training. To show that it is not, we tried variants in which we flip the images left-right (**OURS-MIRROR**), we rotate them by 90 degrees (**OURS-90**) and by 270 degrees (**OURS-270**). As can be seen in Tab. 4, **OURS-MIRROR** performs on par with **OURS-PIX**, the model trained without any image-wise supervision. **OURS-90** and **OURS-270** do slightly better but **OURS** is clearly best. This confirms the importance of flipping the images upside-down, which helps the network deal with perspective effects.

**Cross-Scene Domain Adaptation.** In the experiments described above, we use synthetic data as the source domain. However, we could use unlabeled real-data instead in which the crowd distribution is different from that in the target domain, which is a typical scenario. To explore this option, we proceed as in [21] and use the UCF-

Model	MAE	RMSE
No Adapt [21]	33.95	39.44
Synthetic	29.51	34.79
CSCC [105]	18.05	22.34
CODA [89]	31.39	37.17
SCP [20]	22.79	26.52
EAD [21]	11.23	15.16
<b>OURS+Real</b>	<b>10.26</b>	<b>13.68</b>
<b>OURS+Synthetic</b>	<b>10.02</b>	<b>13.27</b>
Supervised	9.99	14.24

Table 5. **Ablation study on cross-scene domain adaptation.** We tested with cross-scene setting where the source domain is UCF-QNRF dataset and target domain is Venice dataset, both are real image datasets. Our model still consistently outperforms state-of-the-art cross-scene domain adaptation work and even achieve competing performance as the supervised method.

QNRF dataset as the labeled source domain data and the Venice [47] one as unlabeled target domain one. We rely again on the BL [58] backbone network and report our results in Tab. 5. No Adapt and Synthetic denote the BL model trained without any domain adaptation technique with UCF-QNRF and GCC respectively. Since the crowd distribution in GCC is closer to the Venice one than the one in UCF-QNRF, Synthetic still does a little better than UCF-QNRF. **OURS+Synthetic** is our model trained with the synthetic data, as we did in the rest of the paper, whereas **OURS+Real** is a variant in which we replaced the synthetic data by the real images of UCF-QNRF. The difference is much less, but **OURS+Synthetic** does slightly better, again on account of the more similar crowd distribution. Note that we are *not* claiming that synthetic data is better than real data in general. Our point is that, for the real data to provide effective training, the crowd distribution in it should be mirror that of the test images.

## 5. Conclusion

We have proposed an approach to combining image-wise and pixel-wise self-supervision to substantially increase cross-domain crowd counting performance when only synthetic data and real-data without annotations are available. We demonstrated excellent results that approach those of fully supervised methods.

The domain adaptation scheme we developed treats the synthetic data as the source data. However, if annotated real-data were available, it could also be used for this purpose. In future work, we will therefore expand it to leverage both synthetic images and multiple real-world image datasets with partial annotations.

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