

Point in, Box out: Beyond Counting Persons in Crowds

Yuting Liu¹, Miaoqing Shi², Qijun Zhao¹, Xiaofang Wang²

¹Biometrics Research Laboratory, College of Computer Science, Sichuan University

²Univ Rennes, Inria, CNRS, IRISA



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Crowd Counting



➡ #persons ?

Related Works

**Regression-based
Counting**

**Detection-based
Counting**

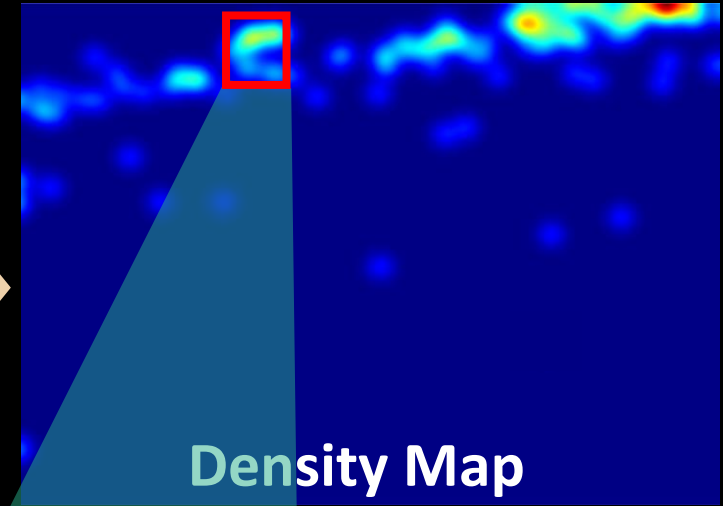
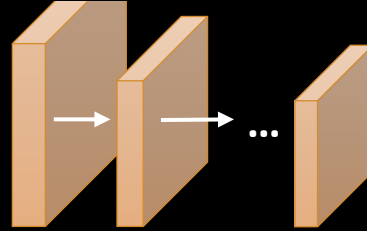
Related Works

Annotation Cost

Low



Regression-based
Counting



Density Map

Output Information

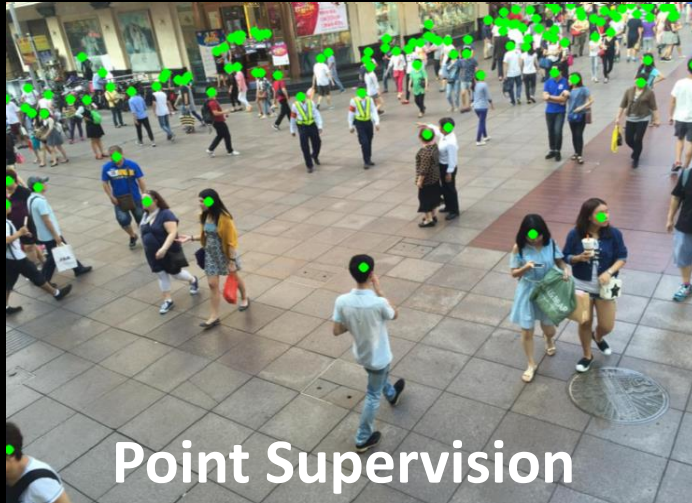
Coarse

Can not detect the persons
(Tracking, Recogniton, ...)

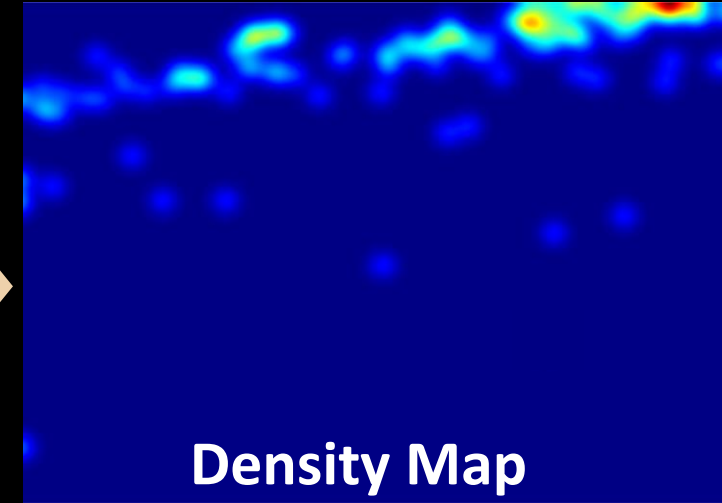
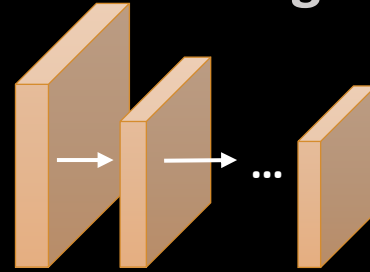
Related Works

Annotation Cost

Low



Regression-based Counting

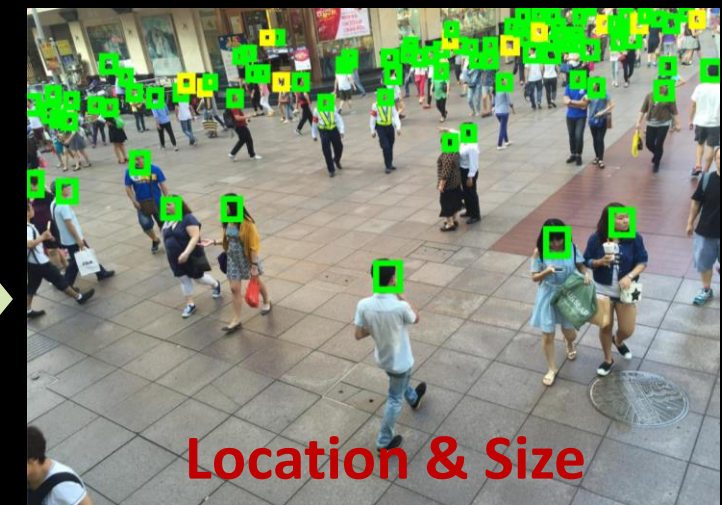
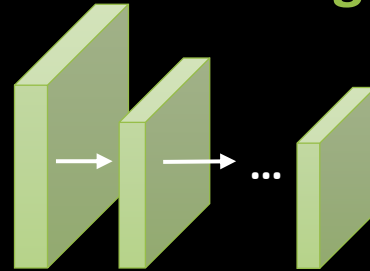


Coarse

High



Detection-based Counting

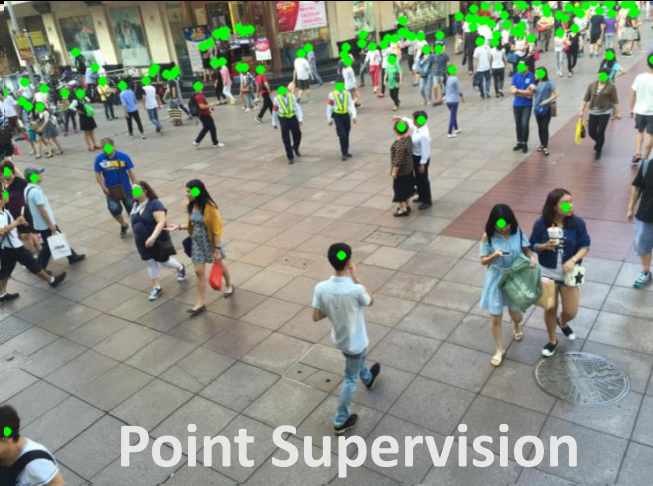


Fine

Our Goal: Point In, Box Out

Annotation Cost

Low



Our proposed PSDDN:

- Pseudo GT Initialization
- Online Pseudo GT Updating
- Locally-constrained Regression Loss
- Curriculum Learning

Output Information



Fine

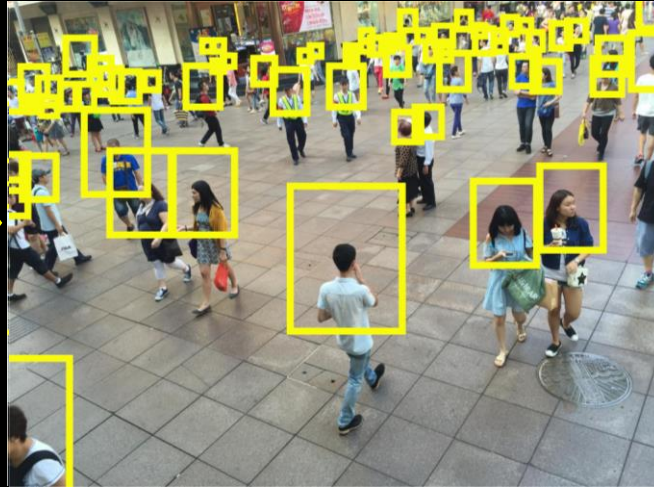
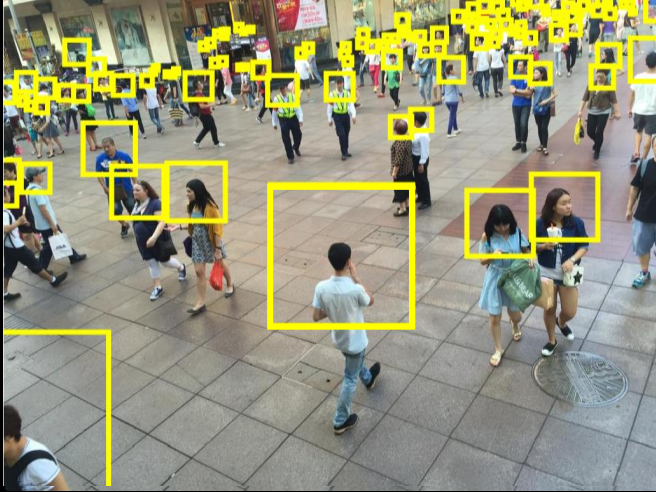
Our Approach: Overview

Annotation Cost

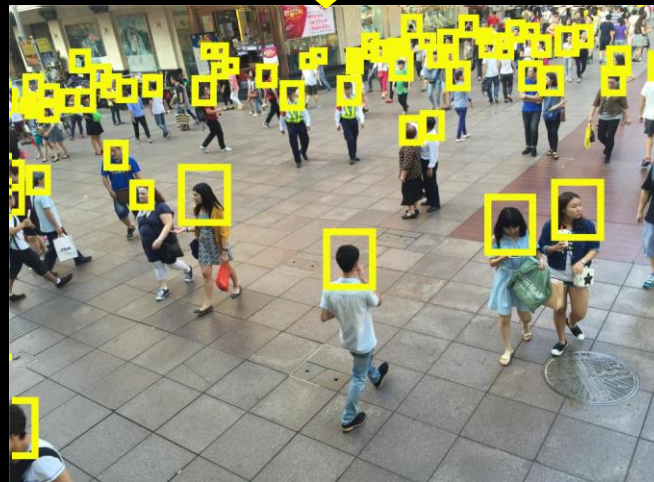
Pseudo GT Updating

Output Information

Low



Pseudo GT Initialization



Location & Size

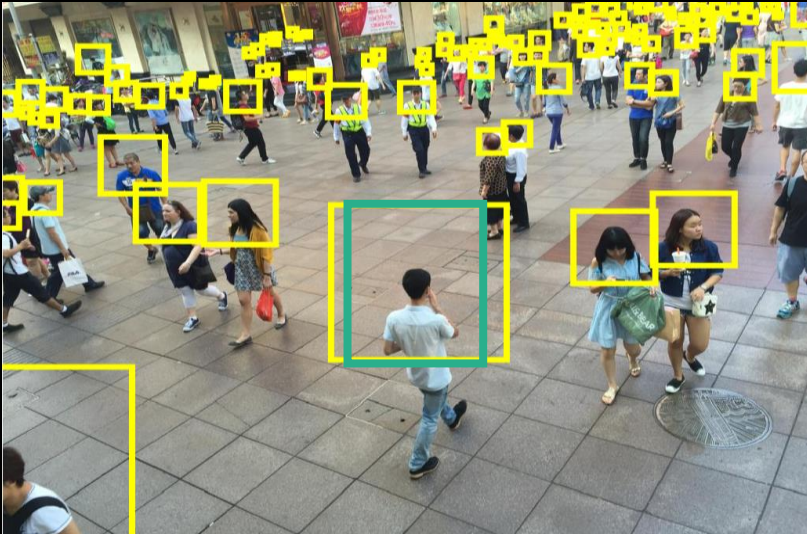
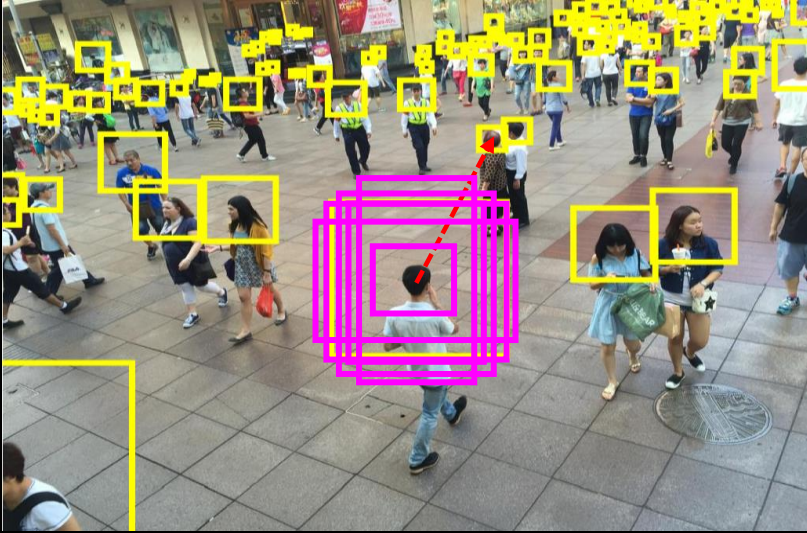
Fine

Our Approach: Pseudo GT Initialization



Nearest neighbor distances indeed
reflects head **size information**

Our Approach: Online Pseudo GT Updating



- 1) Select positive anchors:

$$IOU(pos(g^t), g^t) > 0.7 \ \&\& \ SIZE((pos(g^t))) < d(g, NN_g)$$

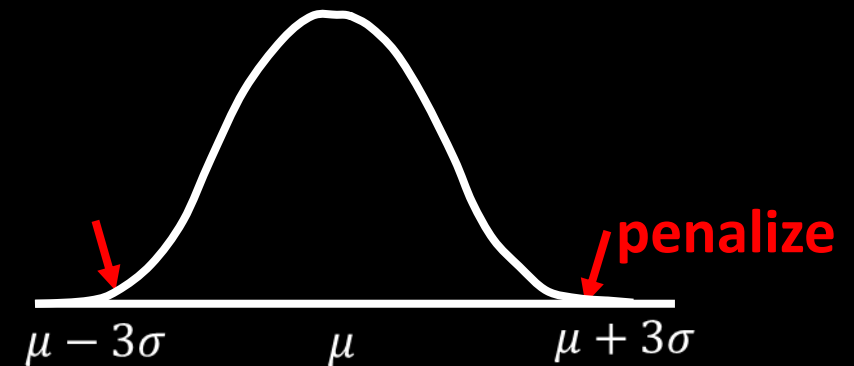
- 2) g^{t+1} is from those $pos(g^t)$ that has the **highest detection score**

$(g^t$: Pseudo GT at t^{th} iteration; $pos(g^t)$: positive anchors of g^t ; $d(g, NN_g)$: distance from g to its nearest neighbor head; $SIZE(\cdot)$: smallest side of height or width)

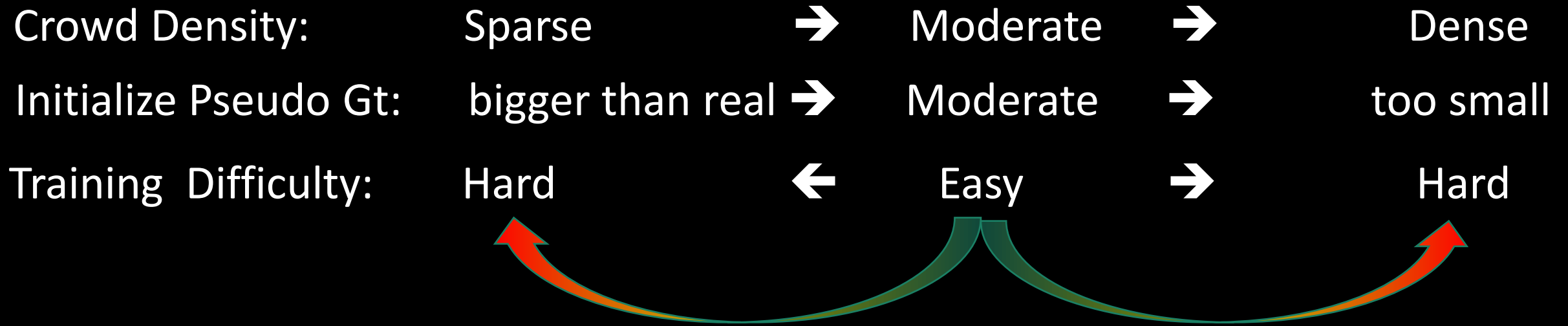
Our Approach: Locally-constrained Regression Loss



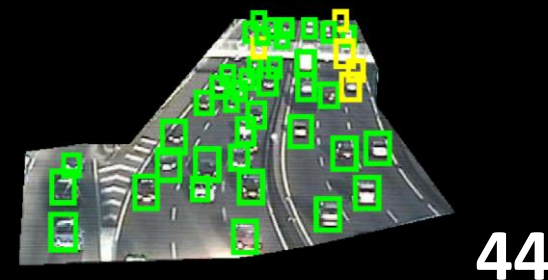
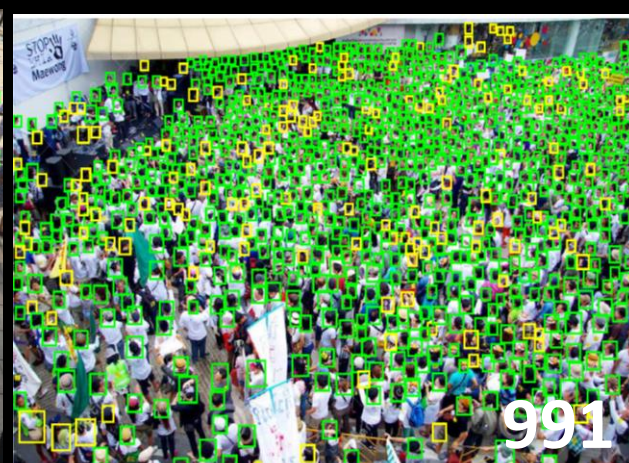
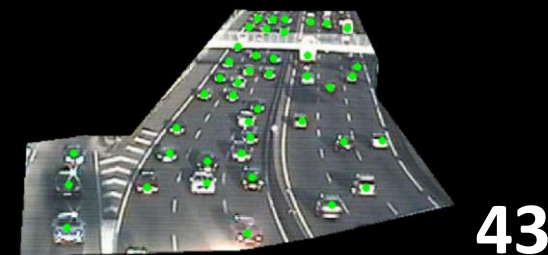
We **penalize** the predicted Bboxes if its size clearly **violate the observation**



Our Approach: Curriculum Learning



Our Results



□ True positives

□ False positives

Our Results

Dataset	SHA		SHB	
Measures	MAE	MSE	MAE	MSE
Pv0	168.6	268.3	69.8	98.1
Pv1	104.7	193.8	41.7	66.6
Pv2	89.8	169.5	19.1	42.4
Pv3(PSDDN)	85.4	159.2	16.1	27.9
PSDDN + [20]	65.9	112.3	9.1	14.2
Li et al. [20]	68.2	115.0	10.6	16.0
Ranjan et al. [31]	68.5	116.2	10.7	16.0
Liu et al. [24]	73.6	112.0	13.7	21.4
Liu et al. [22]	-	-	20.7	29.4
DetNet in [22]	-	-	44.9	73.2
Sindagi et al. [41]	73.6	106.4	20.1	30.1
Sam et al. [35]	90.4	135.0	21.6	33.4

Table 1: Counting: ablation study of PSDDN on ShanghaiTech dataset (Pv0: trained with initialized pseudo GT; Pv1: Pv0 + pseudo GT updating; Pv2: Pv1 + our regression loss; Pv3: Pv2 + curriculum learning).

Dataset	Pv0	Pv1	Pv2	Pv3 (PSDDN)
SHA	0.308	0.491	0.539	0.554
SHB	0.015	0.241	0.582	0.663

Table 2: Detection: ablation study of PSDDN on ShanghaiTech dataset. AP is reported.

Methods	Annotations	WiderFace		
		easy	medium	hard
Avg. BB	points(test)+ mean size	0.002	0.083	0.059
FR-CNN (ps)	points(train) + mean size	0.008	0.183	0.108
FR-CNN (fs)	bounding boxes (train)	0.840	0.724	0.347
PSDDN	points(train)	0.605	0.605	0.396

Table 3: Detection results on WiderFace. (AP)

Methods	GAME0	GAME1	GAME2	GAME3	AP
Victor et al. [19]	13.76	16.72	20.72	24.36	-
Onoro et al. [27]	10.99	13.75	16.09	19.32	-
Li et al. [20]	3.56	5.49	8.57	15.04	-
PSDDN	4.79	5.43	6.68	8.40	0.669

Table 4: Counting and detection results on TRANCOS dataset. GAME and AP are reported.

Thank you!

Poster: #32