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# 1. Unsupervised Cross-Domain Crowd Counting

≻ Goal

 Transfer source domain pre-trained counting model to target domains using unlabeled data.





- Pre-trained model is inferior in practice due to different data distributions.
- Annotation is expensive and laborious.



Target domain

# 1. Unsupervised Cross-Domain Crowd Counting

- ➢ Challenge
  - How to explore concealed information in unlabeled data for knowledge transfer from source domain to unseen target domains?
  - How to measure the reliability of supervision signal?

#### Solutions

- Regard density isomorphism reconstruction as self-supervised signal.
- Model reconstruction erroneousness using estimation-reconstruction consistency.

> 2.1 Algorithm I: Density Isomorphism Reconstruction



> 2.1 Algorithm II: Reconstruction Erroneousness Modeling



**Error-Aware Density Isomorphism Reconstruction** 

> 2.2 The Proposed Framework



> 2.2 The Proposed Framework

• Input:

Image tuple  $\mathcal{I}_i^d = {\mathbf{I}_{i-d}, \mathbf{I}_i, \mathbf{I}_{i+d}}$  with time interval d, where  $\mathbf{I}_i$  is the image frame at time i.

Density and Erroneousness Inference Module:

Estimate a density map  $\mathbf{D}_i \in \mathbb{R}_{\geq 0}^{W_D \times H_D}$  and erroneousness matrix  $\mathbf{E}_i \in \mathbb{R}_{>0}^{W_D \times H_D}$  for each image  $\mathbf{I}_i$ .

Isomorphism Reconstruction Module:

Generate a reconstructed density map  $\mathbf{D}_{i}^{i-d'}$  (or  $\mathbf{D}_{i}^{i+d'}$ ) for the i-th image using  $\mathbf{D}_{i-d}$  (or  $\mathbf{D}_{i+d}$ ).

> 2.2 The Proposed Framework

#### • Reconstruction Erroneousness Modeling Module:

Simultaneously minimize an density isomorphism reconstruction error and maximize an estimation-reconstruction consistency.

> 2.3 Key Technique I: Density Isomorphism Reconstruction

(1). Calculate image mapping matrix

$$\mathbf{M}_{i}^{j^{*}} = \underset{\mathbf{M}_{i}^{j}}{\operatorname{argmin}} \|\mathbf{I}_{i} - \rho(\mathbf{I}_{j}, \mathbf{M}_{i}^{j})\|^{2},$$
(3)

(2). Convert image mapping matrix to density mapping mapping matrix

$$\mathbf{G}_{i}^{i-d}(u,v) = \mathbf{M}_{i}^{i-d} \left( \frac{W_{I}}{W_{D}} u, \frac{H_{I}}{H_{D}} v \right) \cdot \sqrt{\frac{W_{D}^{2} + H_{D}^{2}}{W_{I}^{2} + H_{I}^{2}}}, \quad (4)$$
$$\mathbf{G}_{i}^{i+d}(u,v) = \mathbf{M}_{i}^{i+d} \left( \frac{W_{I}}{W_{D}} u, \frac{H_{I}}{H_{D}} v \right) \cdot \sqrt{\frac{W_{D}^{2} + H_{D}^{2}}{W_{I}^{2} + H_{I}^{2}}}. \quad (5)$$

> 2.3 Key Technique I: Density Isomorphism Reconstruction

(3). Reconstruct density map according to mapping matrices

$$\mathbf{D}_{i}^{i-d'}(x,y) = \mathbf{D}_{i-d}(u,v), \forall (x,y) = \mathbf{G}_{i}^{i-d}(u,v), \quad (6)$$
$$\mathbf{D}_{i}^{i+d'}(x,y) = \mathbf{D}_{i+d}(u,v), \forall (x,y) = \mathbf{G}_{i}^{i+d}(u,v), \quad (7)$$

> 2.3 Key Technique II: Reconstruction Erroneousness Modeling

 $\mathcal{L}(\mathcal{I}_i^d) = \mathcal{L}_{iso}(\mathcal{I}_i^d) + \mathcal{L}_{mod}(\mathcal{I}_i^d),$ 

(1) Error-aware density isomorphism reconstruction objective:

$$\mathcal{L}_{iso}(\mathcal{I}_{i}^{d}) = \left\| \left\| \mathbf{D}_{i} - \mathbf{D}_{i}^{i-d'} \right\|_{e} \otimes \mathbf{E}_{i-d} \right\|^{2} + \left\| \left\| \mathbf{D}_{i} - \mathbf{D}_{i}^{i+d'} \right\|_{e} \otimes \mathbf{E}_{i+d} \right\|^{2},$$

$$\mathbf{D}_i \in \mathbb{R}^{W_D imes H_D}_{\geq 0}$$
  
 $\mathbf{E}_i \in \mathbb{R}^{W_D imes H_D}_{>0}$ 

(8)

(2) Erroneousness matrix regularization term

$$\mathcal{L}_{mod}(\mathcal{I}_i^d) = \log(\mathbf{E}_{i-d}) + \log(\mathbf{E}_{i+d})$$

#### > 2.4 Experiment:

Supervision	Method	Venice		UCSD		MALL		FDST	
		MAE↓	MSE↓	MAE↓	MSE↓	MAE↓	MSE↓	MAE↓	MSE↓
	Baseline	33.95	39.44	7.96	8.54	4.27	5.94	4.77	8.33
Supervised	PFlow	15.00	19.60	0.81	1.07		_	2.84	3.57
	BL	9.99	14.24	0.84	1.08	1.54	2.00	1.42	1.88
Semi-supervised	SSR	19.84	31.13	1.68	2.07	2.69	3.38	5.41	6.13
	FSSA	17.83	25.24	1.45	<u>1.85</u>	2.32	2.97	2.96	3.86
Unsupervised	CSCC	18.05	22.34	8.89	9.87	4.01	4.99	5.15	7.84
	CODA	31.39	37.17	5.25	6.07	3.37	4.43	4.74	8.27
	SCP	22.79	26.52	4.55	5.71	3.03	4.04	4.28	6.74
	Ours-w/o mod	14.66	17.48	2.22	2.71	3.17	4.03	3.97	4.76
	Ours	11.23	15.16	1.79	2.47	2.36	3.12	3.25	3.94

Table 1: Performance Evaluation on Four Benchmark Datasets.

> 2.4 Experiment:



Figure 3: Influence of different d values.

#### > 2.4 Experiment:

Source	Method	Venice		UCSD		MALL		FDST	
		MAE↓	MSE↓	MAE↓	MSE↓	MAE↓	MSE↓	MAE↓	MSE↓
ShanghaiTech-A	Baseline-MESA	51.57	53.68	16.80	17.81	15.67	16.75	12.80	25.59
	Ours	17.83	22.19	5.13	5.83	5.57	6.54	6.27	7.64
	Baseline-BL	40.13	51.54	15.36	16.18	12.48	12.99	5.01	8.09
	Ours	14.10	19.13	4.22	5.01	4.77	5.93	3.96	5.12
UCF-QNRF	Baseline-MESA	43.16	57.88	9.04	9.77	5.71	6.67	6.12	7.57
	Ours	13.05	15.72	2.64	3.60	4.65	6.01	4.95	6.10
	Baseline-BL	33.95	39.44	7.96	8.54	4.27	5.94	4.77	8.33
	Ours	11.23	15.16	1.79	2.47	2.36	3.12	3.25	3.94

Table 2: Robustness to Different Pre-trained Models.

> 2.4 Experiment:



**Redundant Counting** 

# Thank you