Semi-Supervised Domain Adaptation for Wildfire Detection

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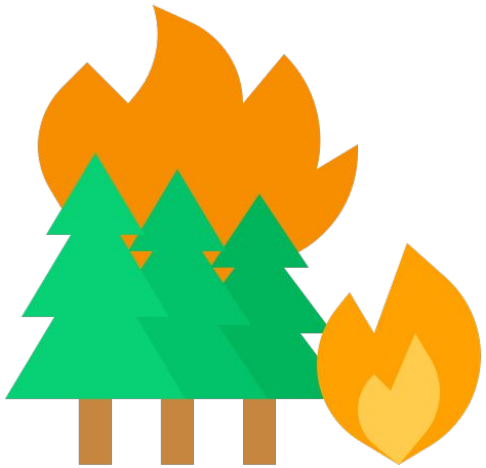
alchera

2023 Wildfire Statistics for USA

34.1K fires



15.1M
acres

National Interagency Fire Center (NIFC)

Damage caused by wildfires

Lahaina, Hawaii, Aug. 8, 2023

2K
homes

$ 4 ~ 6
billion

115 death

2.7K
acres

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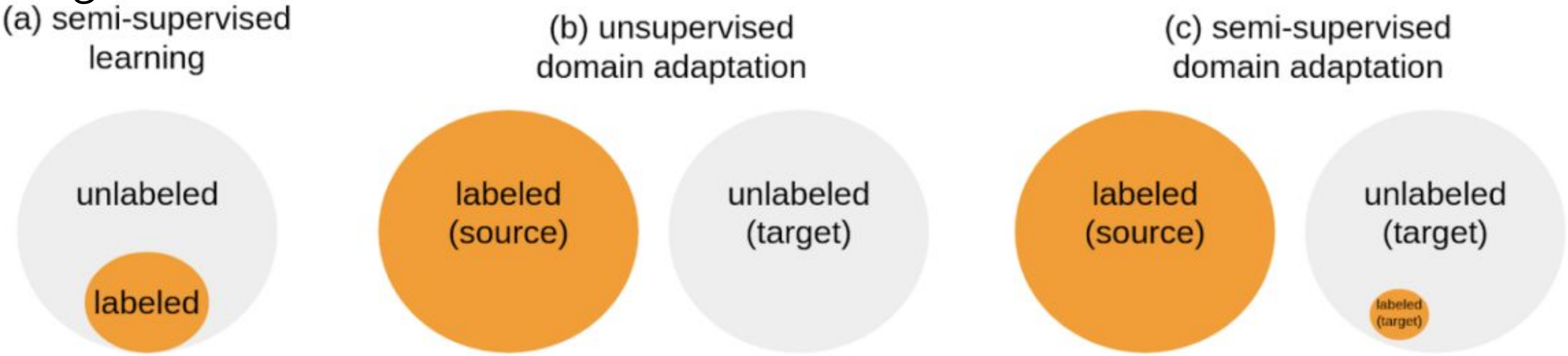
➔ Early Wildfire Detection could prevent such damages

Effects on Climate Change

- Number of Catastrophic wildfires annually increasing
- Global warming exacerbates such wildfires by making soils warmer
- Saving Forests could delay global warming which store Carbons

Why we need Semi-Supervised Domain Adaptation?

- Domain shift occurs for Training & Testing environment
- Limited number of <u>target domain</u> images allowed
- Enhance the performance by using state-of-the-art SSL and UDA algorithms



Dataset
HPWREN (High Performance Wireless Research and Education Network)

- Opensource wildfire dataset gathered by HPWREN
  - fixed-view camera, S. California, 101 cameras, high-resolution images

	Previous labels	Proposed labels	Total HPWREN
# of directories	9	283	342
# of images	609	2,575	27,174

- The label is provided in a limited manner
  - We propose <u>additional labels</u> & <u>protocols</u> for semi-supervised domain

	source	target 0.5%	target 1.0%	target 3.0%	target validation
foreground images	309	44	94	257	451
background images	300	58	111	359	630
total images	609	102	205	616	1,081

download link: https://www.hpwren.ucsd.edu/HPWREN-FIgLib/HPWREN-FIgLib-Data/

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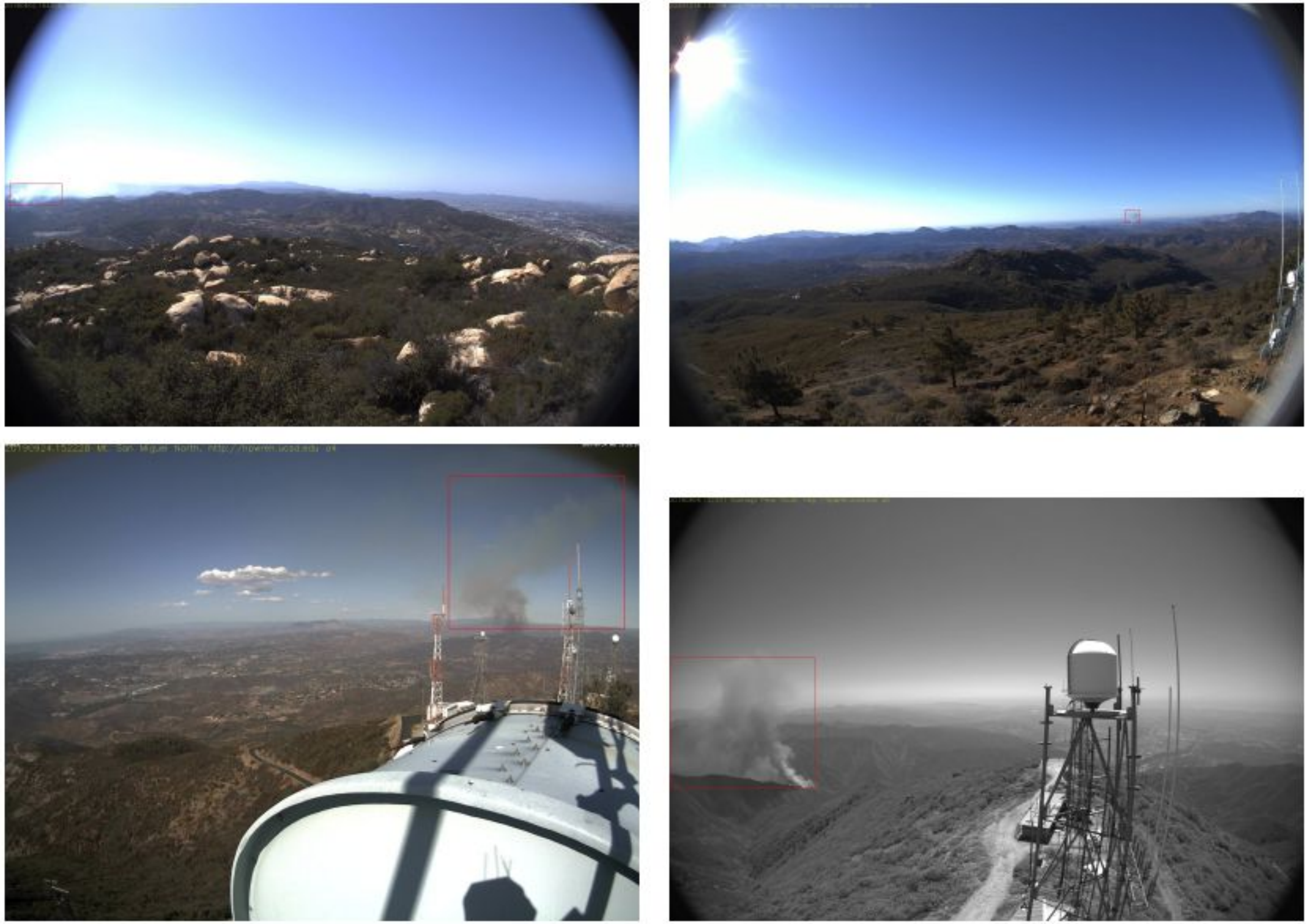
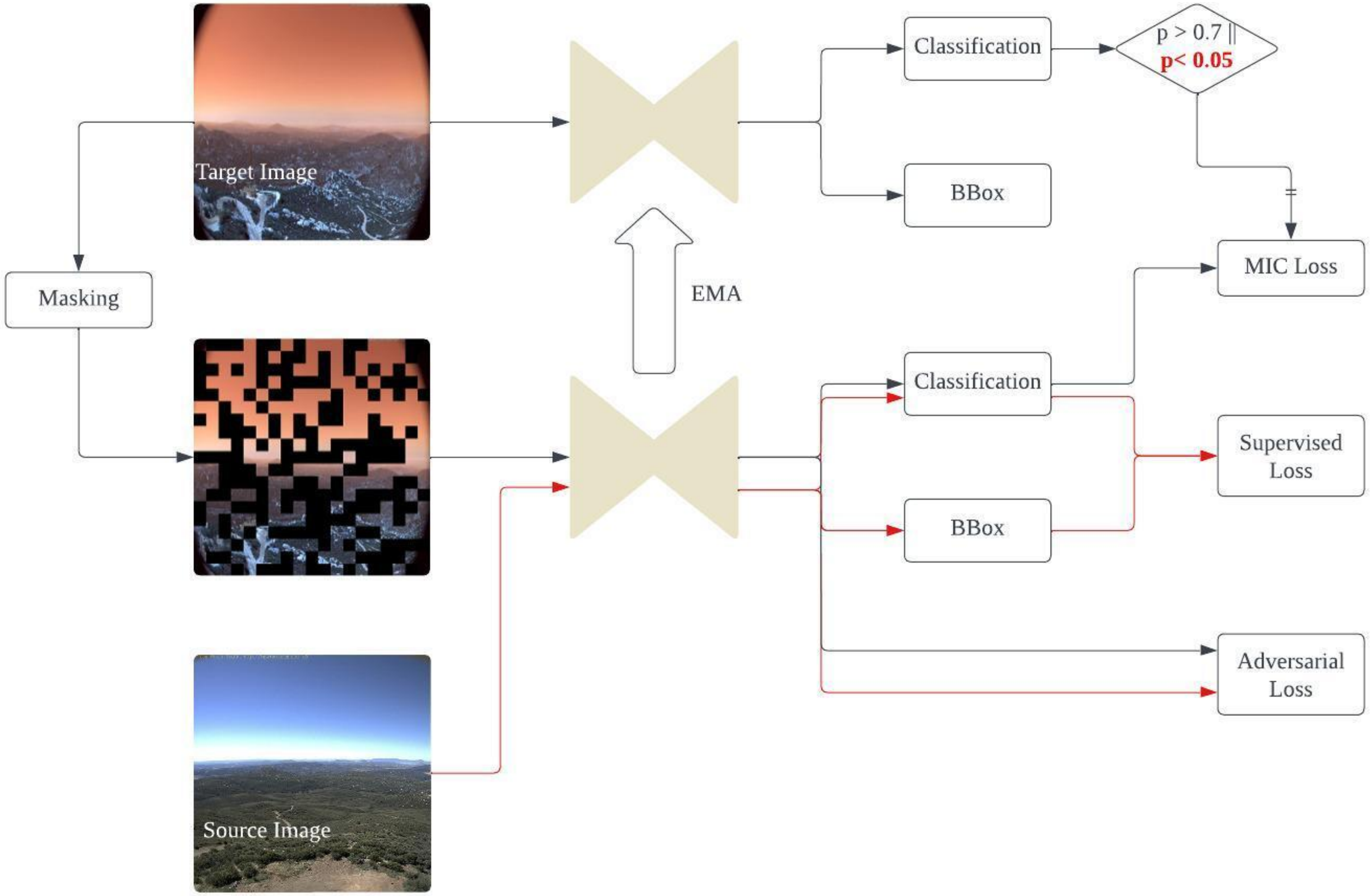


LADA: Location Aware Domain Adaptation

- Overall Diagram



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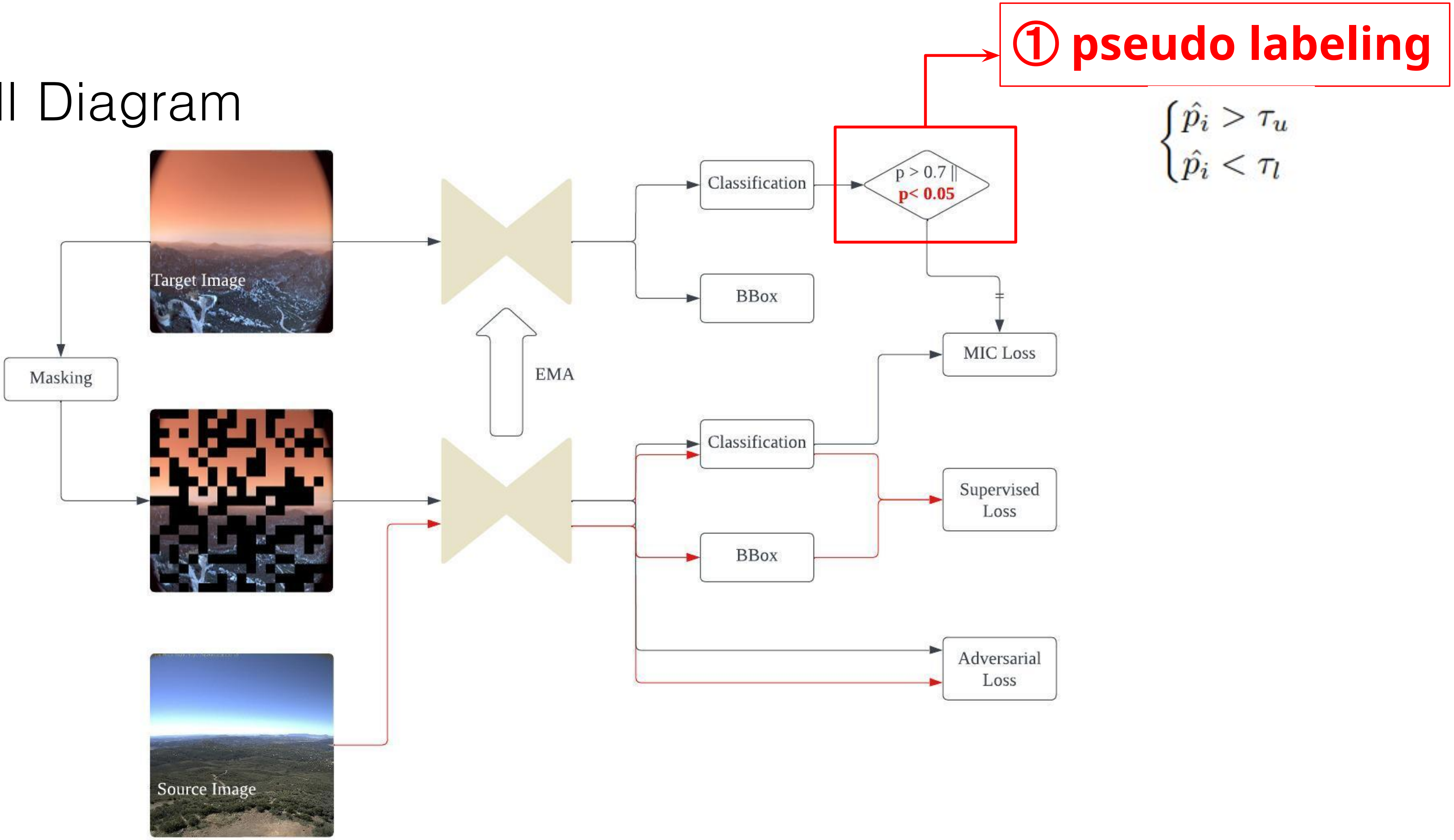

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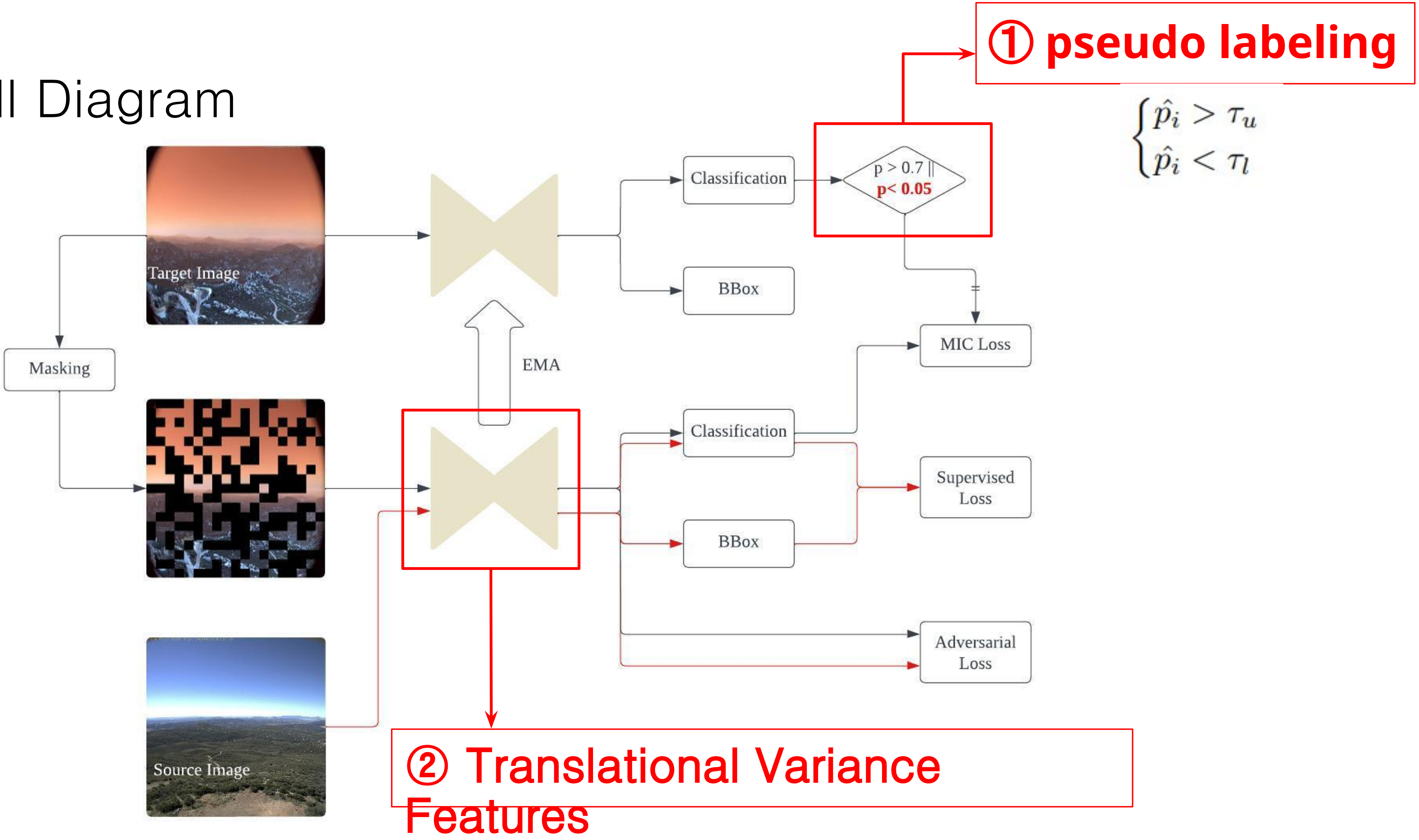
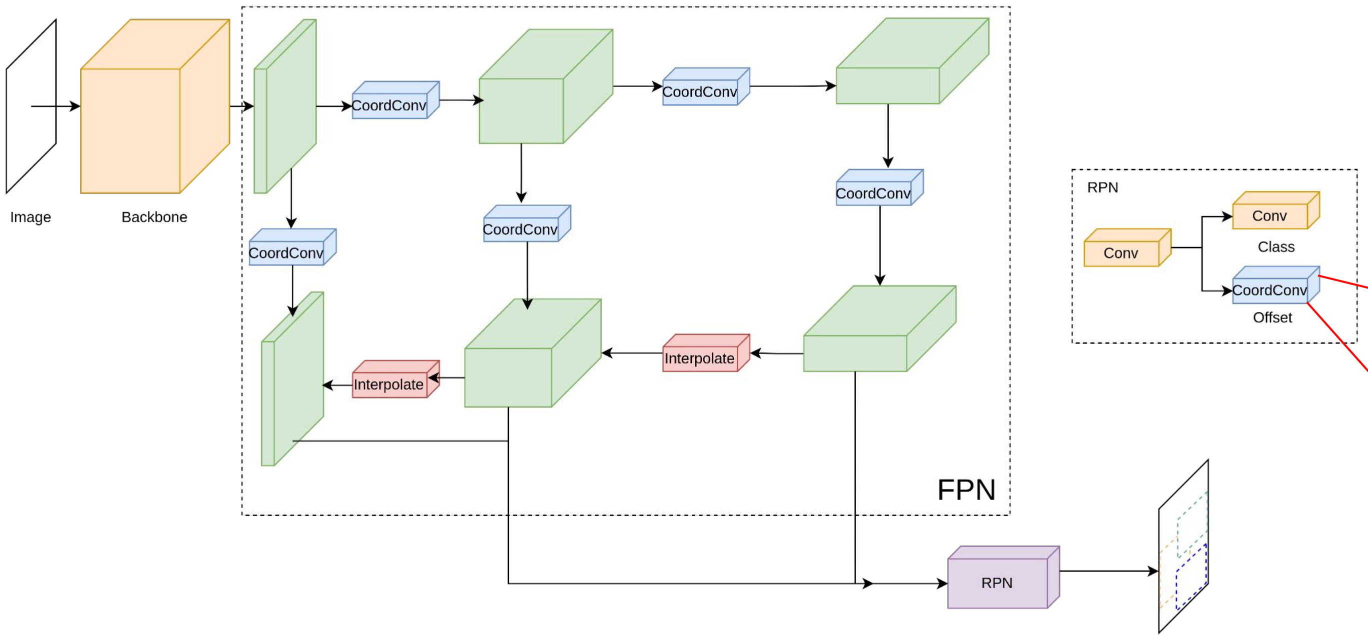
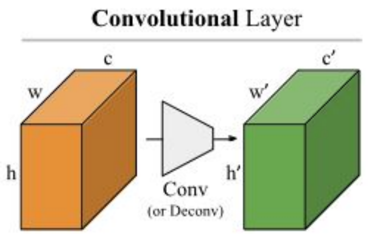


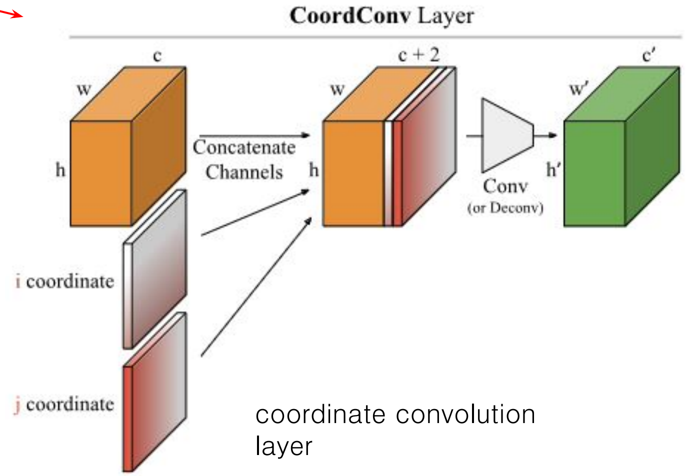
LADA: Location Aware Domain Adaptation
Translational Variance Features

- Additional two conv. channels extracts translational variance features
- Distinguish patterns of appearance dependent on location (position)





original convolution layer



coordinate convolution layer

Liu, et. al, An intriguing failing of convolutional neural networks and the coordconv solution. NIPS, 2018

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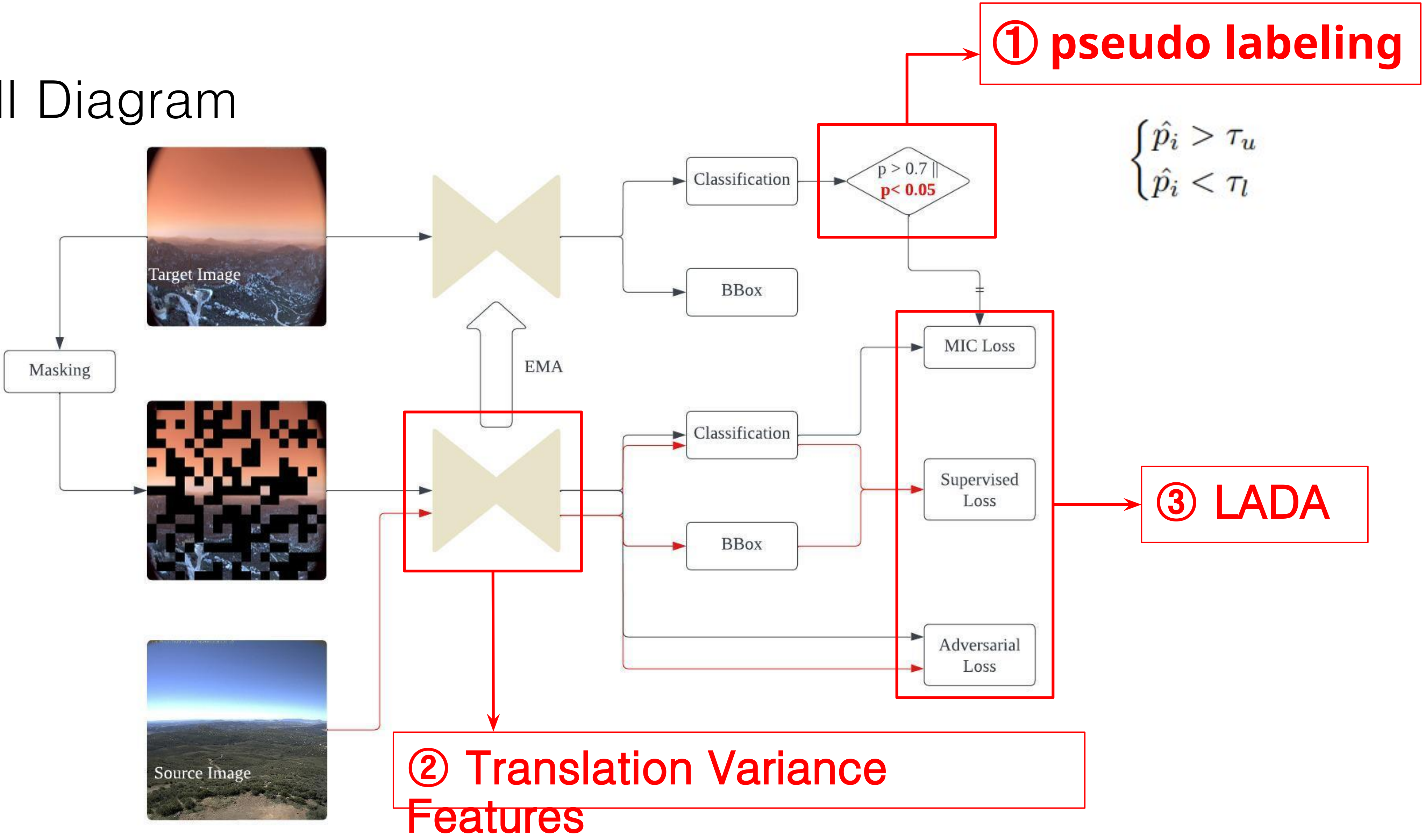

$$\begin{cases} \hat{p}_i > \tau_u \\ \hat{p}_i < \tau_l \end{cases}$$

LADA: Location Aware Domain Adaptation

- Objective Functions

$$min_{\theta_s} \frac{1}{N_s} \sum_{k=1}^{N_s} L_k^S + \frac{1}{N_t} \sum_{k=1}^{N_t} (\lambda^M L_k^M) + \frac{1}{N_t + N_s} \sum_{k=1}^{N_t+N_s} (\lambda^A L_k^A + \lambda^C L_k^C)$$

  - supervised loss
    - Use labeled source data

$$\boxed{L^S = L_{det} = L_{cls} + L_{loc}}$$

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  - masked consistency loss
    - align masked & unmasked image output

$$\boxed{x^M = \mathcal{M} \odot x^T} \quad \boxed{\hat{y}^M = f_\theta(x^M)} \quad \boxed{\mathcal{L}^M = q^T \mathcal{H}(\hat{y}^M, p^T)}$$

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  - adversarial loss
    - align source and target domain

$$\boxed{\begin{aligned} &L^A = L_{img} + L_{ins} \\ &L_{img} = \sum_{l=1}^{L} \sum_{P_{(u,v)}^L \in P^L} [z log p_{(u,v)}^l + (1-z) log(1 - p_{(u,v)}^s)] \\ &L_{ins} = \sum_{l=1}^{L} \sum_{Q_i^l \in Q^l} [z log p_i^l + (1-z) log(1 - p_i^s)] \end{aligned}}$$

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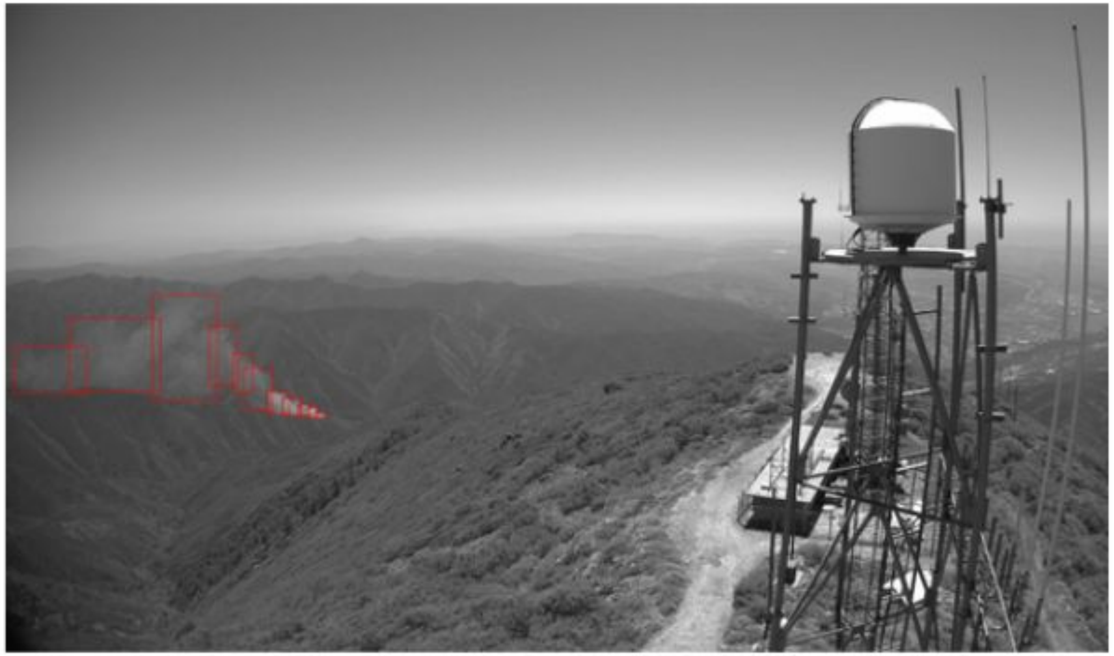
  - consistency loss
    - align domain predictions for instance & image le

$$\boxed{L_{cst} = \sum_{Q_i \in Q} || \frac{1}{|C|}_{C_{(u,v)}} p_{(u,v)} - p_i ||_1}$$

Results

- Ablation study – labeling policy (mAP / mAP@0.5)

	0.5%	1.0%	3.0%
original label	1.5/7.0	2.8/12.9	7.9/29.6
propsed label	7.9/24.0	10.2/31.5	18.8/48.4



original label

proposed label

Results

- SSDA result (mAP / mAP@0.5)

Type	Methods	Label target images		
		0.5%	1.0%	3.0%
Source-only	SADA	6.9/21.9	9.7/28.7	17.8/48.0
	LADA	**7.9/24.0**	**10.2/31.5**	**18.8/48.4**
SSDA	SADA	9.7/27.3	12.3/34.9	20.4/53.0
	LADA	**10.0/29.1**	**14.0/38.0**	**20.9/52.3**

- Conclusion
  - Propose Semi-supervised Domain Adaptation benchmark for Object Detection
  - Suggest robust baseline for SSDA-OD named LADA