



# TeSLA: Test-Time Self-Learning With Automatic Adversarial Augmentation

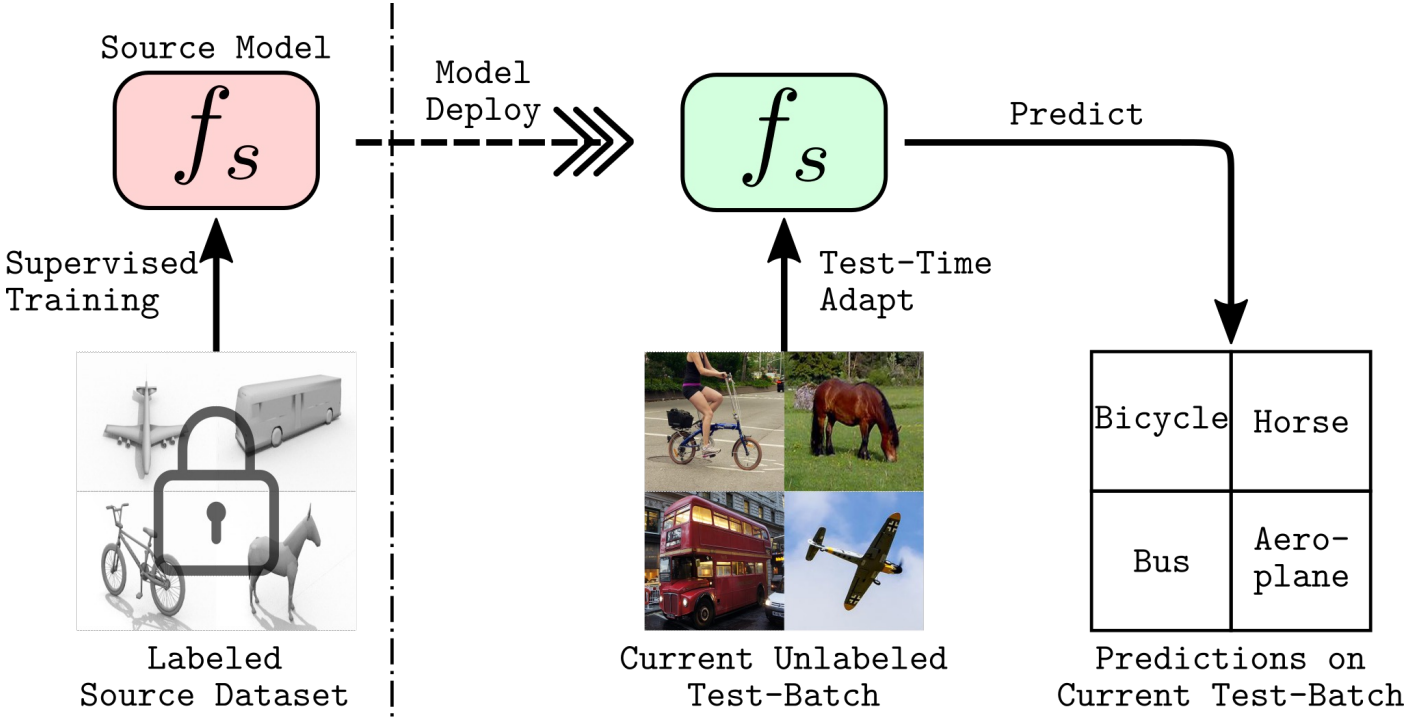
Join us in the poster session: THU-AM-367

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# Test-Time Adaptation (TTA)

- Adapt the pre-trained **source model** to the *distributionally shifted* test domain
- Access to the **source training dataset** is restricted

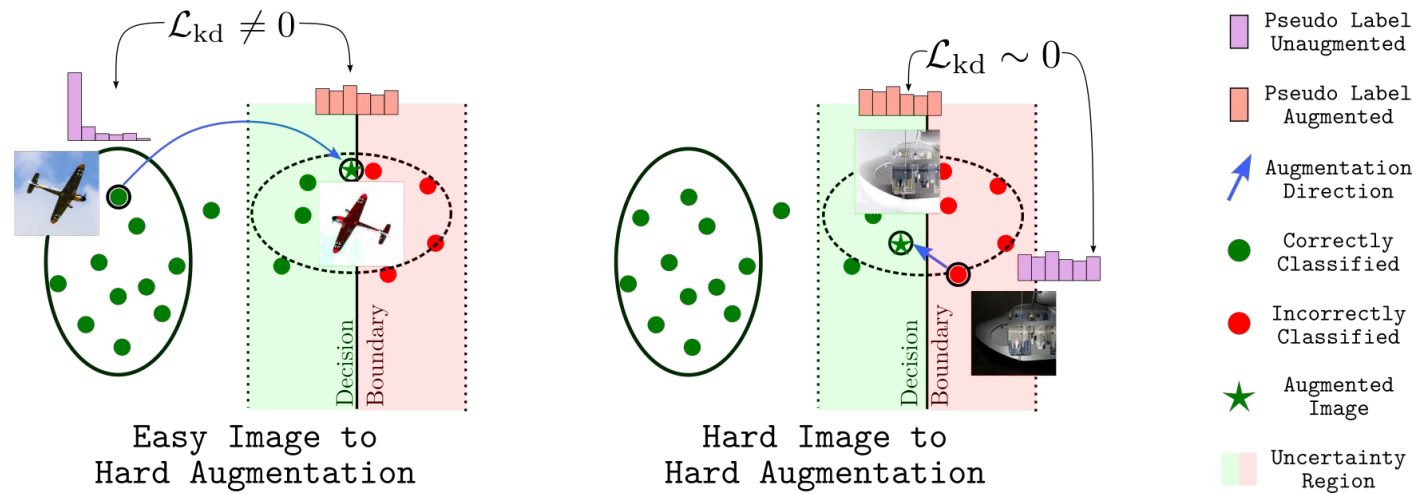


# TTA: shortcomings of current methods

- Poor model calibration
- Special model architectures and source training strategies
- Dataset and task-specific methods

# TeSLA: motivation

- Simulate hard-to-classify images using adversarially augmented test images



# TeSLA: summary of results

**Class avg. error rates (%) on classification task**

Method	Protocol	Common Image Corruptions						Syn-to-Real		Measurement Shift	
		CIFAR10-C		CIFAR100-C		ImageNet-C		VisDA-C		Kather-16	
		O	M	O	M	O	M	O	M	O	M
Source	N	29.1		60.4		81.8		51.5		32.0	
BN	N	15.6	15.4	43.7	43.3	67.7	67.6	35.4	35.0	18.3	18.2
TENT	N	14.1	12.9	39.0	36.5	57.4	54.2	33.5	29.3	16.2	12.0
SHOT	N	13.9	14.2	39.2	38.7	68.7	68.2	29.4	24.5	14.7	12.0
AdaContrast	N	-						23.1	20.2	-	
TTT++	Y	15.8	9.8	44.4	34.1	59.3	-	35.2	34.1	16.7	7.9
TTAC	Y	13.4	<b>9.4</b>	41.7	33.6	58.7	-	32.2	31.1	9.6	5.5
<b>TeSLA</b>	N	12.5	9.7	38.2	32.9	55.0	<b>51.5</b>	<b>17.8</b>	<b>13.5</b>	<b>9.2</b>	3.3
<b>TeSLA-s</b>	Y	<b>12.1</b>	9.7	<b>37.3</b>	<b>32.6</b>	<b>53.1</b>	-	24.0	17.9	9.9	<b>3.1</b>

**Class avg. dice score (%) on MRI segmentation task**

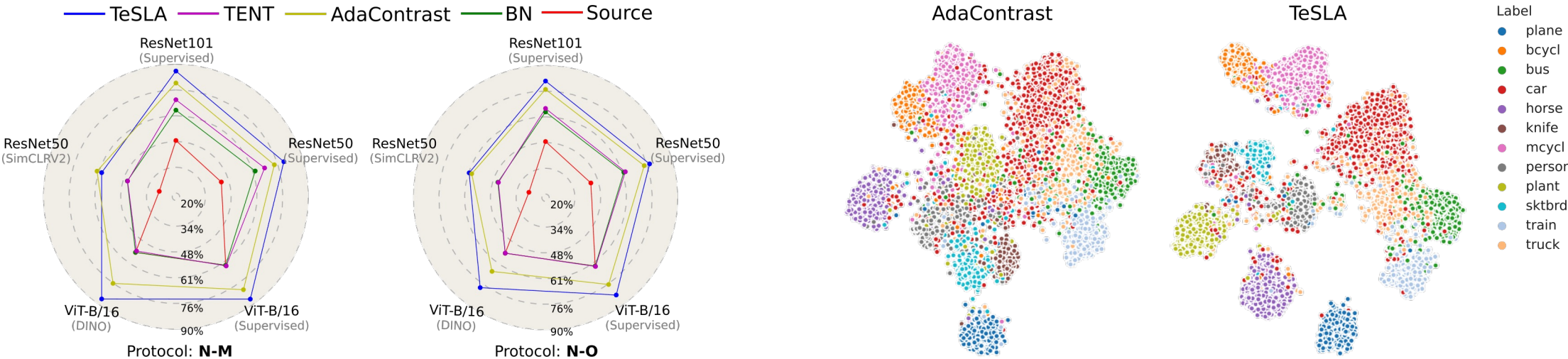
Protocol	Source	BN	TENT	PL	OptTTA	TeSLA
<b>Spinal Cord</b> Site {1} → Sites {2, 3, 4}						
N	O	76.0±11.8	81.6±8.3	81.1±9.1	81.7±8.6	84.1±4.8
N	M		84.3±4.8	84.4±4.7	84.3±4.7	84.3±4.4
N	M					<b>85.4±4.4</b>
<b>Prostate</b> Sites {A, B} → Sites {D, E, F}						
N	O	60.5±27.0	72.1±15.2	74.7±17.9	72.4±15.2	83.1±7.7
N	M		73.1±18.0	81.2±9.3	81.1±9.2	83.4±7.7
N	M					<b>84.3±5.8</b>

**Class avg. mIoU (%) on VisDA-S segmentation task**

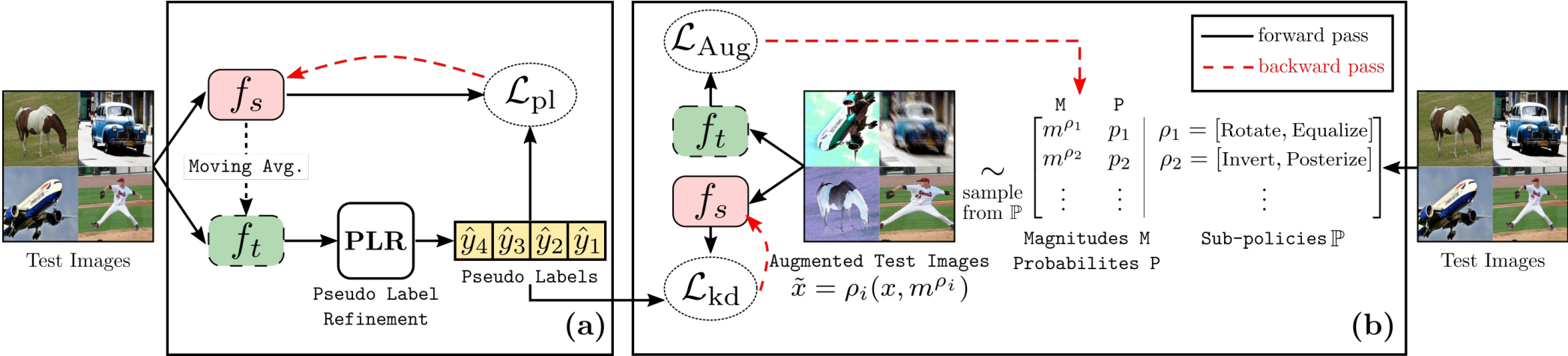
Protocol	Source	BN	TENT	PL	CoTTA	TeSLA
N	O	35.3	36.7	38.3	38.8	37.0
N	M		38.4	39.2	38.6	39.9
N	M					<b>44.5</b>
N	M					<b>46.0</b>

# TeSLA: summary of results

- Agnostic to model architectures and source training strategies
- Better class-wise feature separability

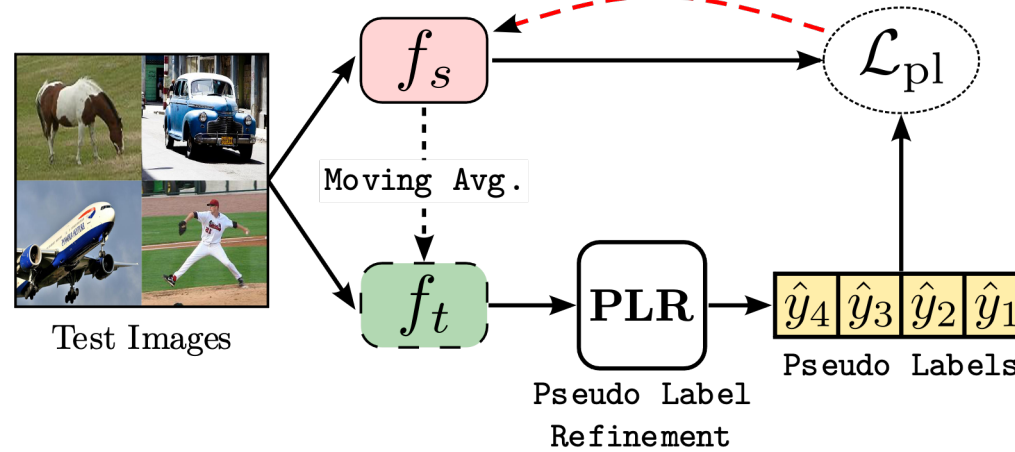


# TeSLA: overview



# Test-time objective

- Flipped cross entropy f-CE as a proxy to teacher-guided mutual information maximization



$$\underbrace{\mathcal{H}(\mathbf{Y}; \hat{\mathbf{Y}} | \mathbf{X})}_{f\text{-CE}} - \mathcal{H}(\mathbf{Y}) = - \underbrace{\mathcal{I}(\mathbf{Y}; \mathbf{X})}_{\text{Mutual Info.}} + \mathcal{D}_{\text{KL}}(\mathbf{Y} \parallel \hat{\mathbf{Y}} | \mathbf{X})$$

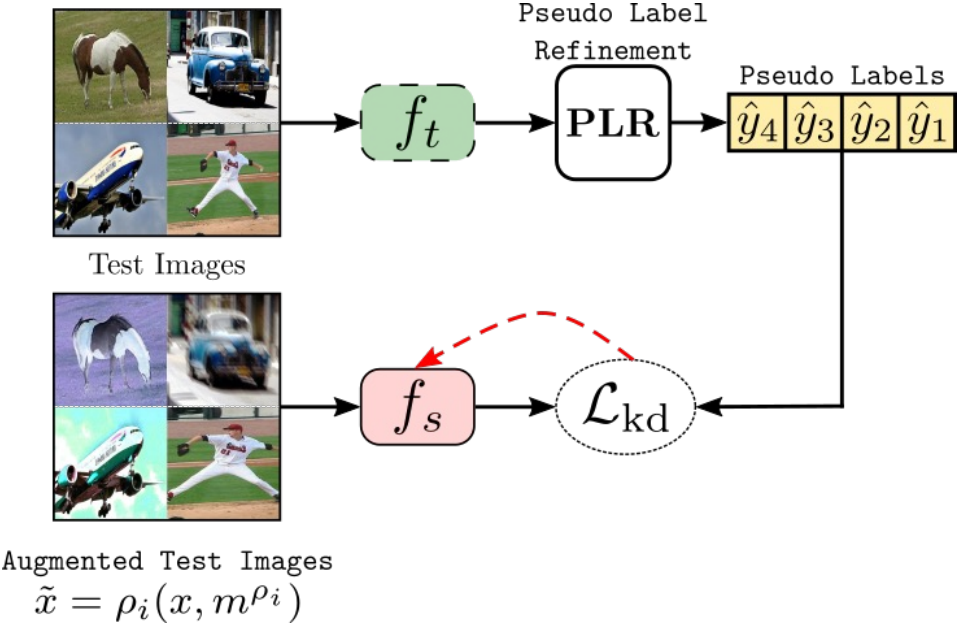
$$\mathcal{L}_{pl}(X, \hat{Y}) = -\frac{1}{B} \sum_{i=1}^B \sum_{k=1}^K (f_s(x_i)_k \log((\hat{y}_i)_k) + \hat{f}_s(X)_k \log(\hat{f}_s(X)_k))$$



# Test-time objective

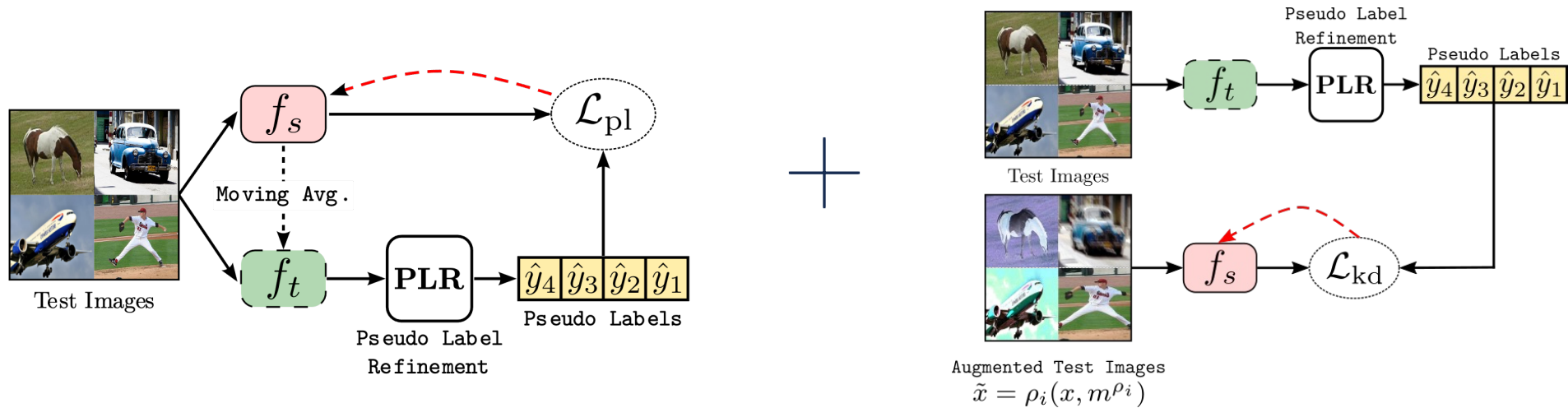
- Knowledge distillation from the teacher to the student using adversarial augmentation

$$\mathcal{L}_{\text{kd}}(\tilde{x}, \hat{y}) = \mathcal{D}_{\text{KL}}(\hat{y} \| f_s(\tilde{x}))$$



# Test-time objective

- Overall test-time objective:



$$\mathcal{L}_{\text{TeSLA}}(X, \tilde{X}, \hat{Y}) = \mathcal{L}_{\text{pl}}(X, \hat{Y}) + \frac{\lambda_2}{B} \sum_{i=1}^B \mathcal{L}_{\text{kd}}(\tilde{x}_i, \hat{y}_i)$$

# PLR (Pseudo Label Refinement)

- Average teacher's predictions on weakly augmented views *stored* in an online balanced queue  $Q$ .

$$\mathbf{z}_t, \mathbf{y}_t \leftarrow \mathbb{E}_{\mathbf{u} \in \rho_w(x)} [g_t(\mathbf{u}), h_t(g_t(\mathbf{u}))]$$

$$Q[\arg \max(\mathbf{y}_t)].\text{append}(\{\mathbf{z}_t, \mathbf{y}_t\})$$

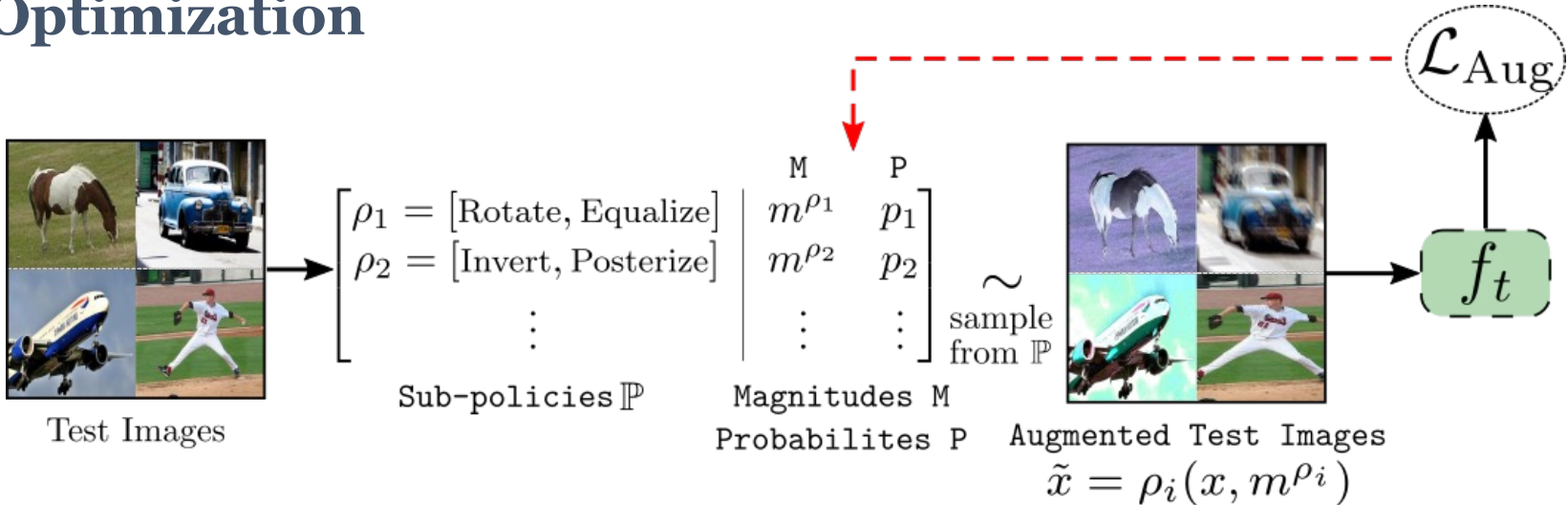
where,  $\rho_w$  denotes weak augmentations,  $g_t$  is the encoder, and  $h_t$  is the classifier

- Refine pseudo-labels by averaging the soft-pseudo labels of k-nearest neighbors from  $Q$ .

$$\hat{y} = \frac{1}{n} \sum \mathcal{N}_{Q,n}(\mathbf{z}_t)$$

# Automatic adversarial augmentations

- **Policy Search Space**
- **Policy Evaluation**
- **Policy Optimization**

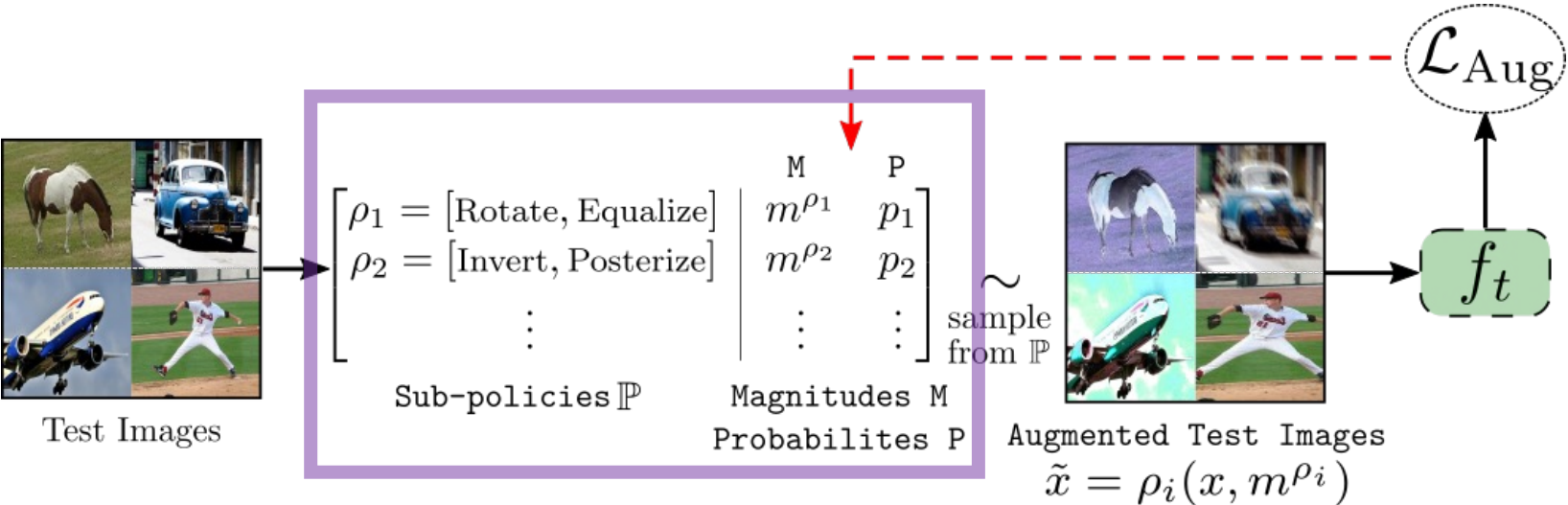


# Automatic adversarial augmentations

## Policy Search Space $\mathbb{P}$

**Sub-policy ( $\rho$ ):** A combination of  $N=2$  image operations and characterized by their magnitudes  $m^\rho$ .

All possible sub-policies with their corresponding magnitudes constitute policy search space.

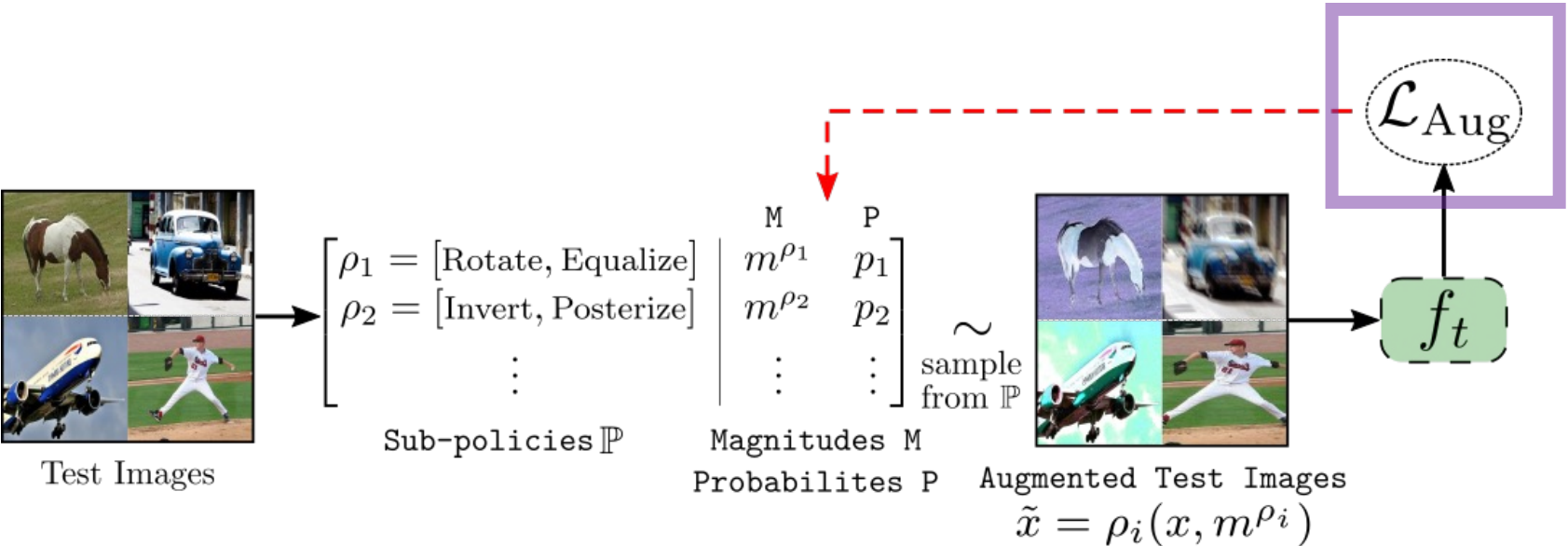


# Automatic adversarial augmentations

## Policy Evaluation

Given teacher  $f_t$ , a sub-policy  $\rho$  with magnitude  $m^\rho$  is evaluated by following loss:

$$\mathcal{L}_{\text{aug}}(\mathbf{x}, \rho) = \sum_{k=1}^K f_t(\tilde{\mathbf{x}}) \log(f_t(\tilde{\mathbf{x}})) + \lambda_1 r(\tilde{\mathbf{x}}, \mathbf{x}) \quad \text{where, } \tilde{\mathbf{x}} = \rho(\mathbf{x}, m)$$

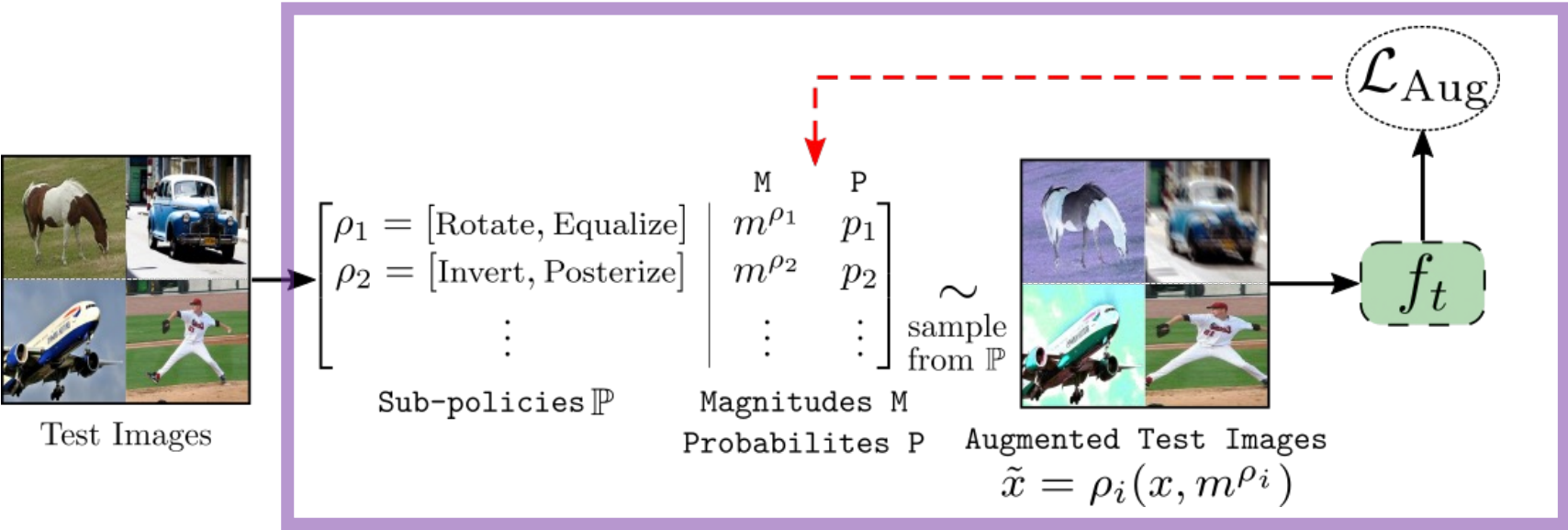


# Automatic adversarial augmentations

## Policy Optimization

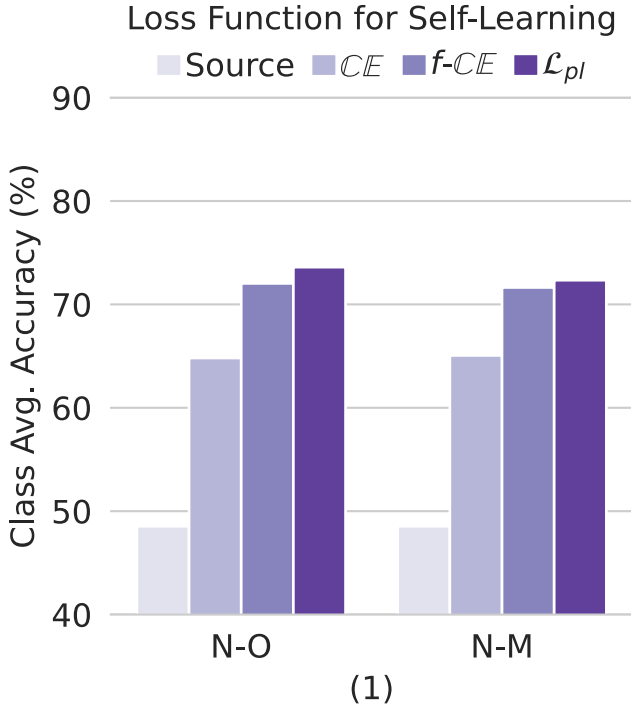
$$\mathbb{E}[\mathcal{L}_{\text{aug}}(x)] = \sum_{i=1}^{|\mathbb{P}|} p_i \cdot \mathcal{L}_{\text{aug}}(x, \rho_i)$$

$$\hat{\delta}(x, \rho_i) = \nabla \mathcal{L}_{\text{aug}}(x, \rho_i) + \mathcal{L}_{\text{aug}}(x, \rho_i) \cdot \nabla \log p_i$$



# Ablation studies: test-time objective

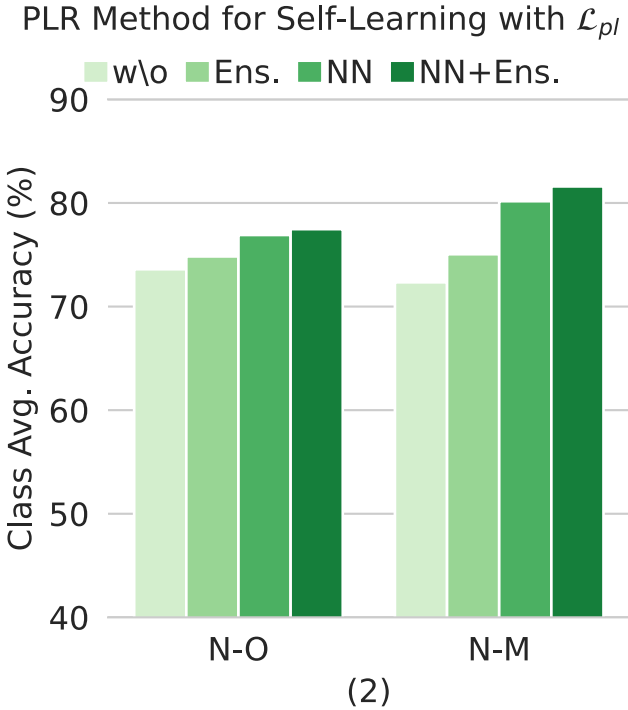
- Our test-time objective outperforms other test-time objectives.





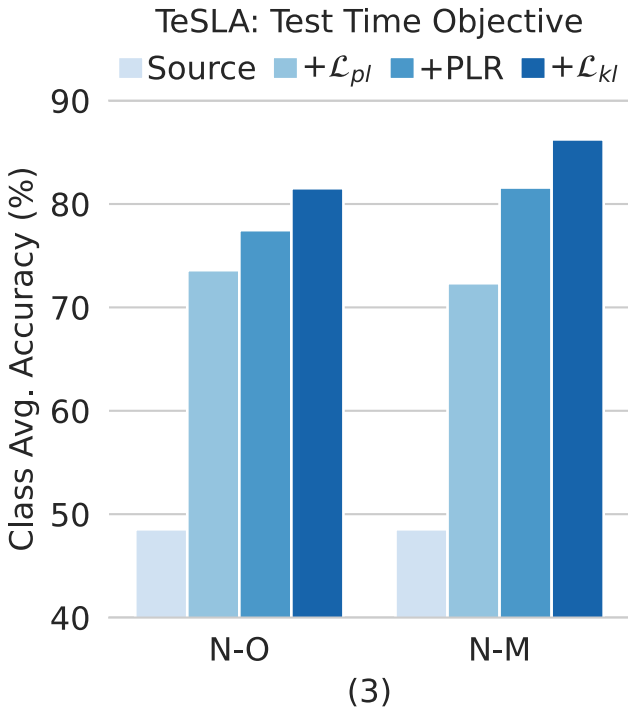
# Ablation studies: PLR

- Our soft-pseudo label refinement module helps to get refined pseudo-labels



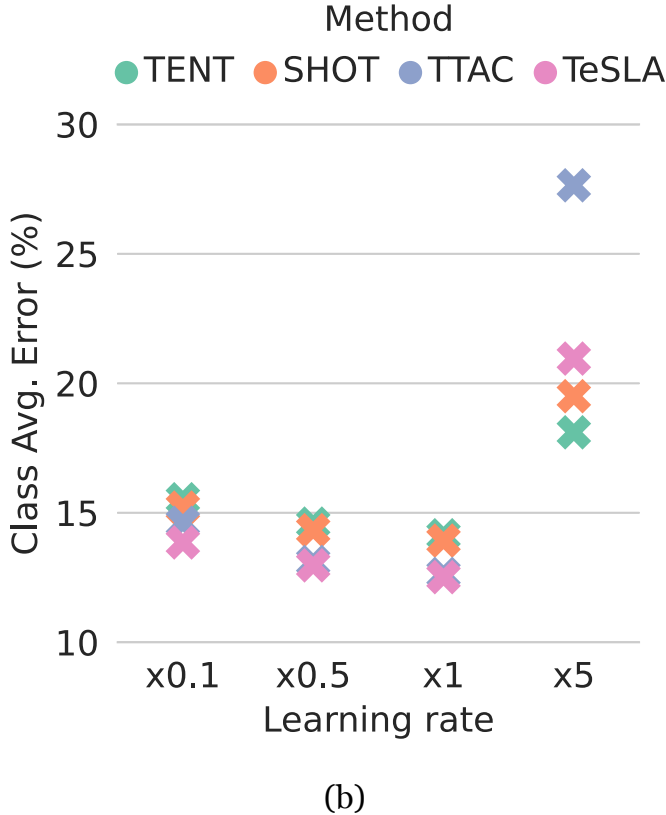
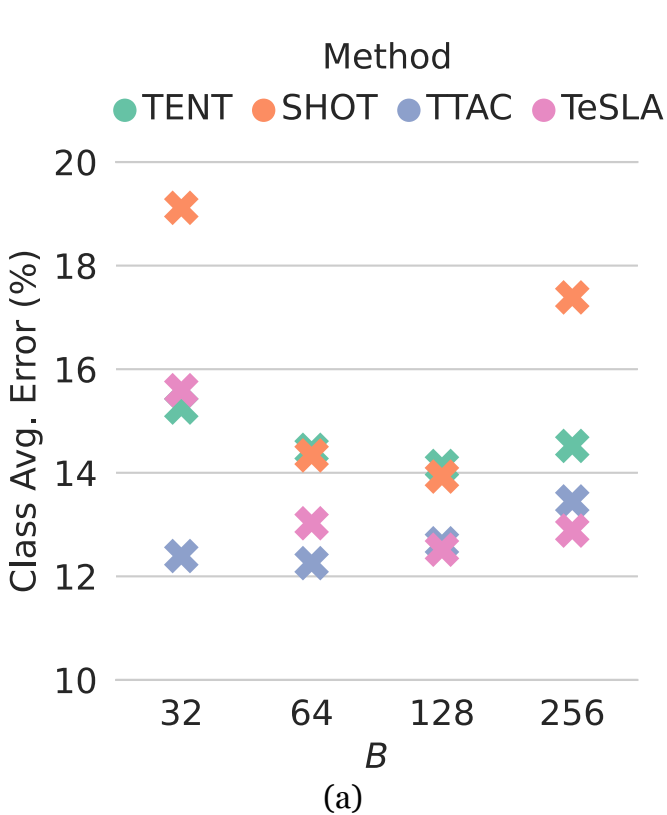
# Ablation studies: individual components

- We study the effect of individual loss term on performance below.



# Ablation studies: sensitivity tests

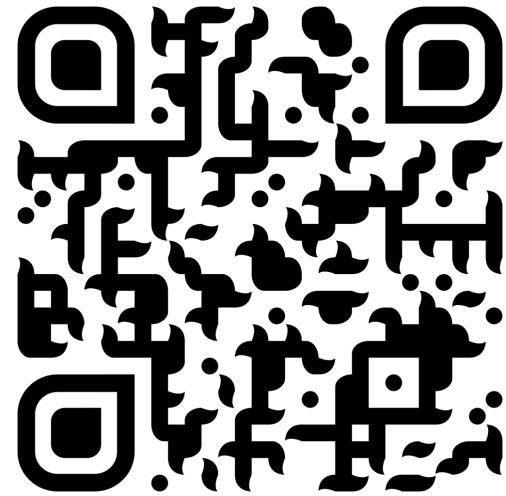
- TeSLA is stable to the change in test-time **(a) batch size** and **(b) learning rate** hyperparameters compared to competing baselines.



# TeSLA: summary and limitations

- Novel self-learning TTA method utilizing efficient automatic adversarial augmentations
- Agnostic to model architectures and source training strategies
- Superior performance from common image corruption to measurement shifts in medical imaging
  
- Assumes test images are class-wise IID distributed!

# Thank You!



Project page: <https://behzadbozorgtabar.com/TeSLA.html>