











HYPOTHESIS → FOR GENERALIZATION ACROSS DOMAIN SHIFTS, WE NEED PER-TEST-IMAGE ADAPTABILITY.



ETHzürich



CV L^{Computer} Vision Lab





Test-Time Adaptation Iterations Concurrent Works PRIOR ON IMAGE PREDICTION STEP PREDICTION STEP PREDICTION STEP PREDICTION STEP SEG. 0 1600 4800 8000 LABELS test_img/gt_dice Karani et al. "Test-time adaptable neural networks for robust medical 0.810 image segmentation." Medical Image Analysis 2021. 0.790 PRIOR ON 0.770 CLASSIFICATION 0.750 LABELS 0.000 2.000k 4.000k 6.000k 8.000k Wang et al. "TENT: Fully Test-time Adaptation by Entropy test img/prior dae dice Minimization." ICLR 2021 0.865 0.855 0.845 PRIOR ON 0.835 0.825 FEATURES 0.815 0.805 Sun et al. "Test-Time Training with Self-Supervision for 0.000 2.000k 4.000k 6.000k 8.000k Generalization under Distribution Shifts." ICML 2020 DAE OUTPUT STEP O DAE OUTPUT STEP DAE OUTPUT STEP DAE OUTPUT STEP GROUND TRUTH 1600 4800 8000 Yufan et al. Self domain adapted network. MICCAI 2020

ML settings	Setup	Source domain		Target domain		Take Home Message (2)
domain shifts		Data	Algorithm	Data	Algorithm	
	Learning a new CNN in each new hospital	$\{\mathbf{x}_{SD}, y_{SD}\}(many)$	$\min_{\theta} L_{SD}^{seg}$	$\{\mathbf{x}_{TD}, y_{TD}\}(many)$	$\min_{\theta} L_{TD}^{seg}$	Adapting a CNN for each test image increases robustness to domain shifts. For image segmentation, a prior on output labels can be used to drive such adaptation.
	Transfer Learning	$\{\mathbf{x}_{SD}, y_{SD}\}(many)$	$\min_{\theta} L_{SD}^{seg}$	$\{\mathbf{x}_{TD}, y_{TD}\}(few)$	Init. at θ_{SD}^* , $\min_{\theta} L_{TD}^{seg}$	
	Unsupervised Domain Adaptation	-	-	$\{\mathbf{x}_{SD}, y_{SD}, x_{TD}\}(many)$	$\min_{\theta} L_{SD}^{seg} + L_{SD,TD}^{inv}$	
	Domain Generalization	$\{\mathbf{x}_{SD}, y_{SD}\}(many)$	$\min_{\theta} L_{SD}^{seg} + L_{SD}^{inv}$	XTI	$\hat{y} = \mathrm{S}_{ heta_{SD}^*}(x_{TI})$	
	Domain Generalization with test time adaptation	${x_{SD}, y_{SD}}(many)$	$\min_{\theta} L_{SD}^{seg} + L_{SD}^{inv}$	XTI	Adapt θ for each test image. $\hat{y} = S_{\theta_{TI}^*}(x_{TI})$	
	Unsupervised Learning	-	-	XTI	Optimize θ for each test image. $\hat{y} = \operatorname{argmax}_{y} P(y) P(x_{TI} y)$	