Unsupervised learning of multimodal image registration using domain adaptation with projected Earth Mover's discrepancies

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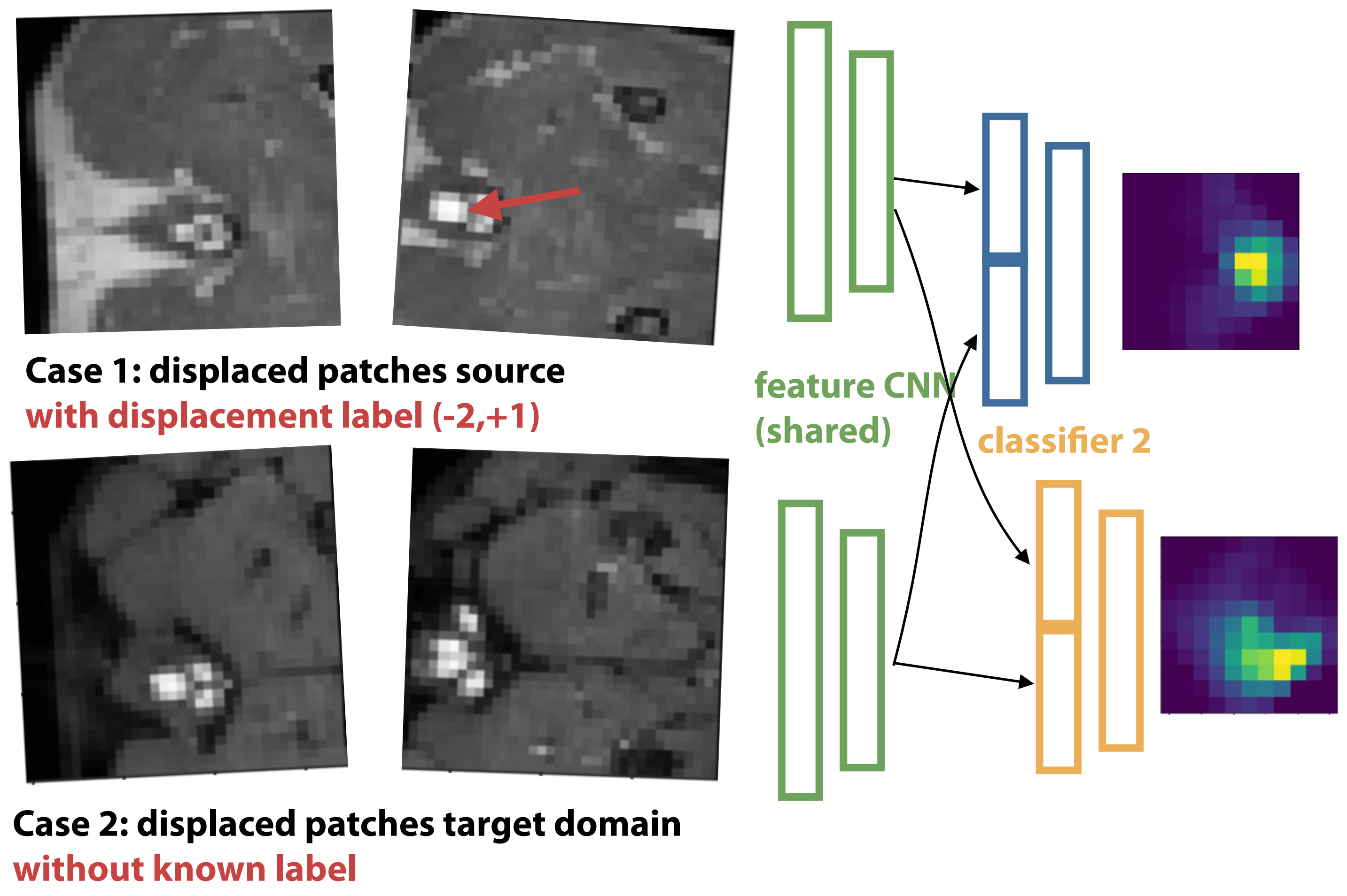
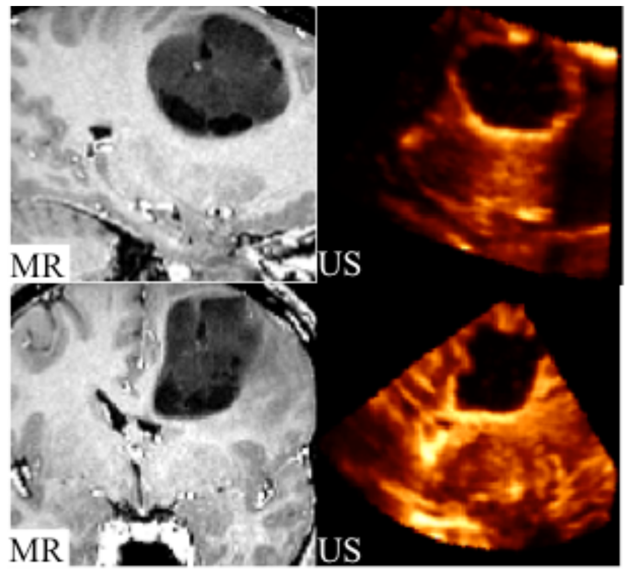
short paper @ MIDL 2020



MIDL
Lübeck 2021
7 - 9 July 2021

see you in Lübeck for MIDL 2021

Motivation and basic concept of multimodal domain adaptation



ultrasound guided brain tumour surgery (MNI McGill)

multimodal registration has clinical impact but **3/3 DL-approaches failed** in CuRIOUS US-MRI registration challenge

open for participation (MICCAI 2020): learn2reg.grand-challenge.org

challenges for multimodal DL registration

1) **features / metrics** (useful for unsupervised DL-reg) **are only well defined for monomodal registration**
2) **ground truth correspondences**/labels across multimodal scans are extremely **rare**

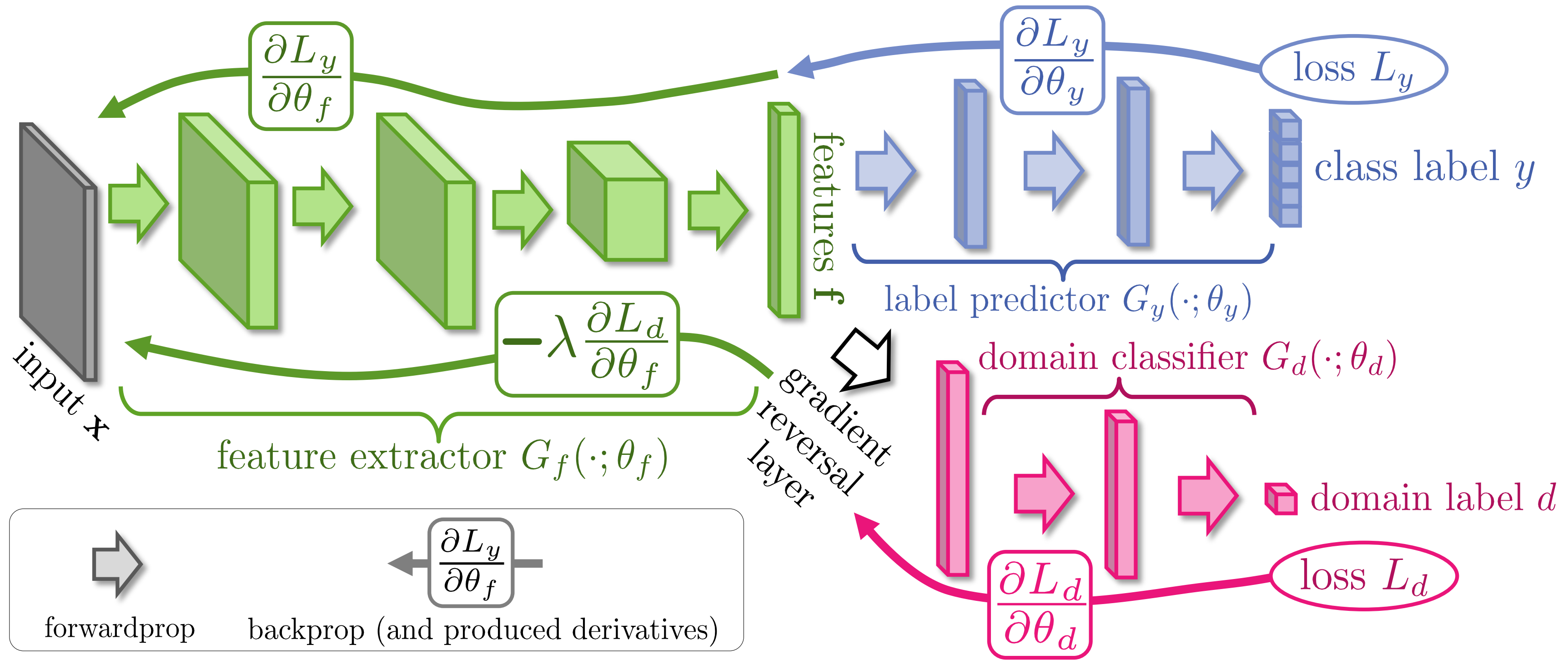
Y Xiao, et al.: Evaluation of MRI to ultrasound registration methods for brain shift correction the CuRIOUS **TMI 2019**

→ **unsupervised domain adaptation** could be ideally suited **to address this problem with deep learning**

contributions of this paper:

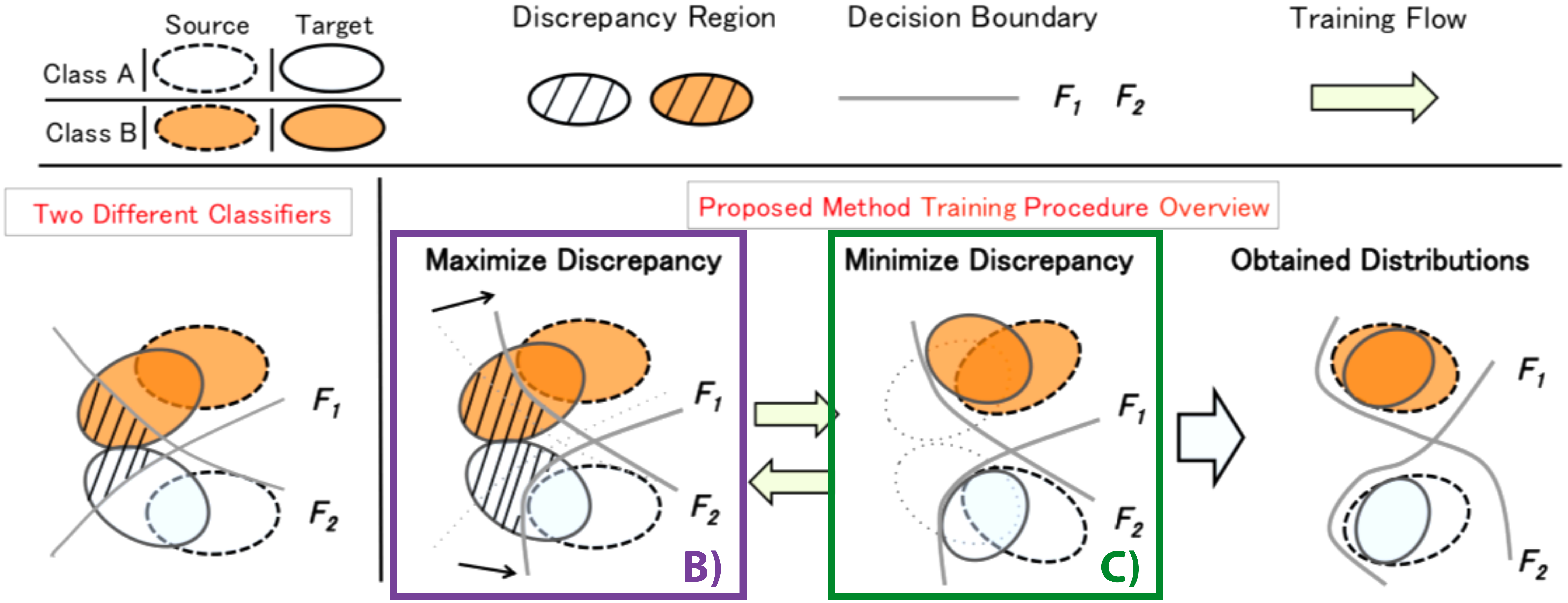
1) employ appropriate setting for domain adaptation for multimodal registration (first time this is done)

2) novel discrepancy metric: projected Earth Mover's (efficient and accurate approximate implementation)



Ganin & Lempitsky: Unsupervised domain adaptation by Backpropagation **ICML 2015**

Discrepancy of classifiers domain adaptation

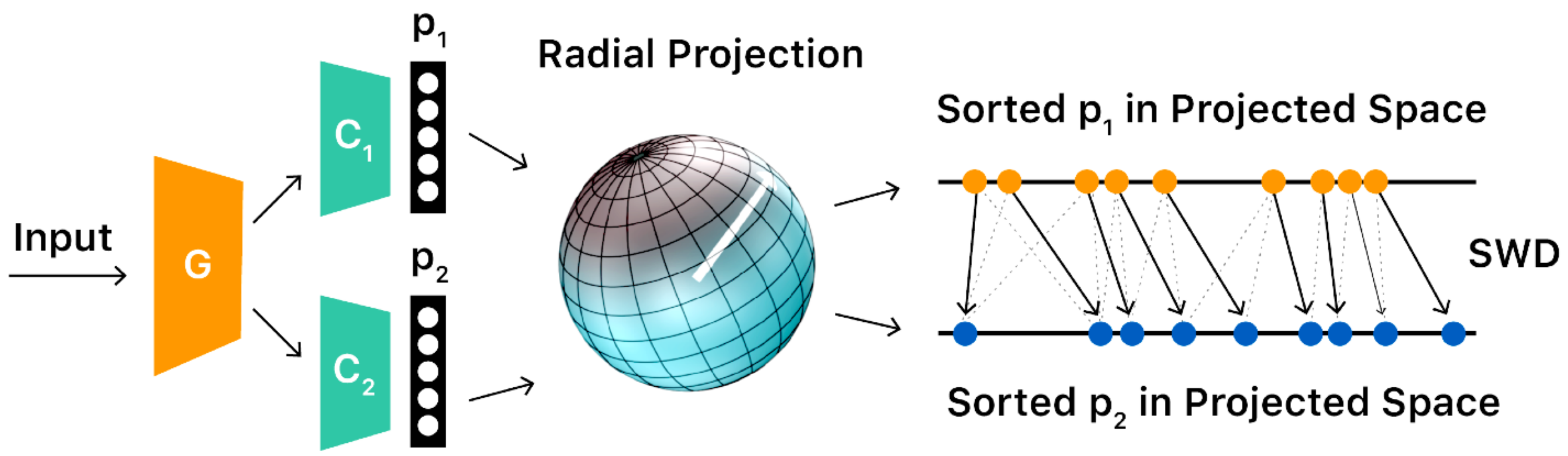


Saito: Maximum Classifier Discrepancy for Unsupervised Domain Adaptation **CVPR 2018**

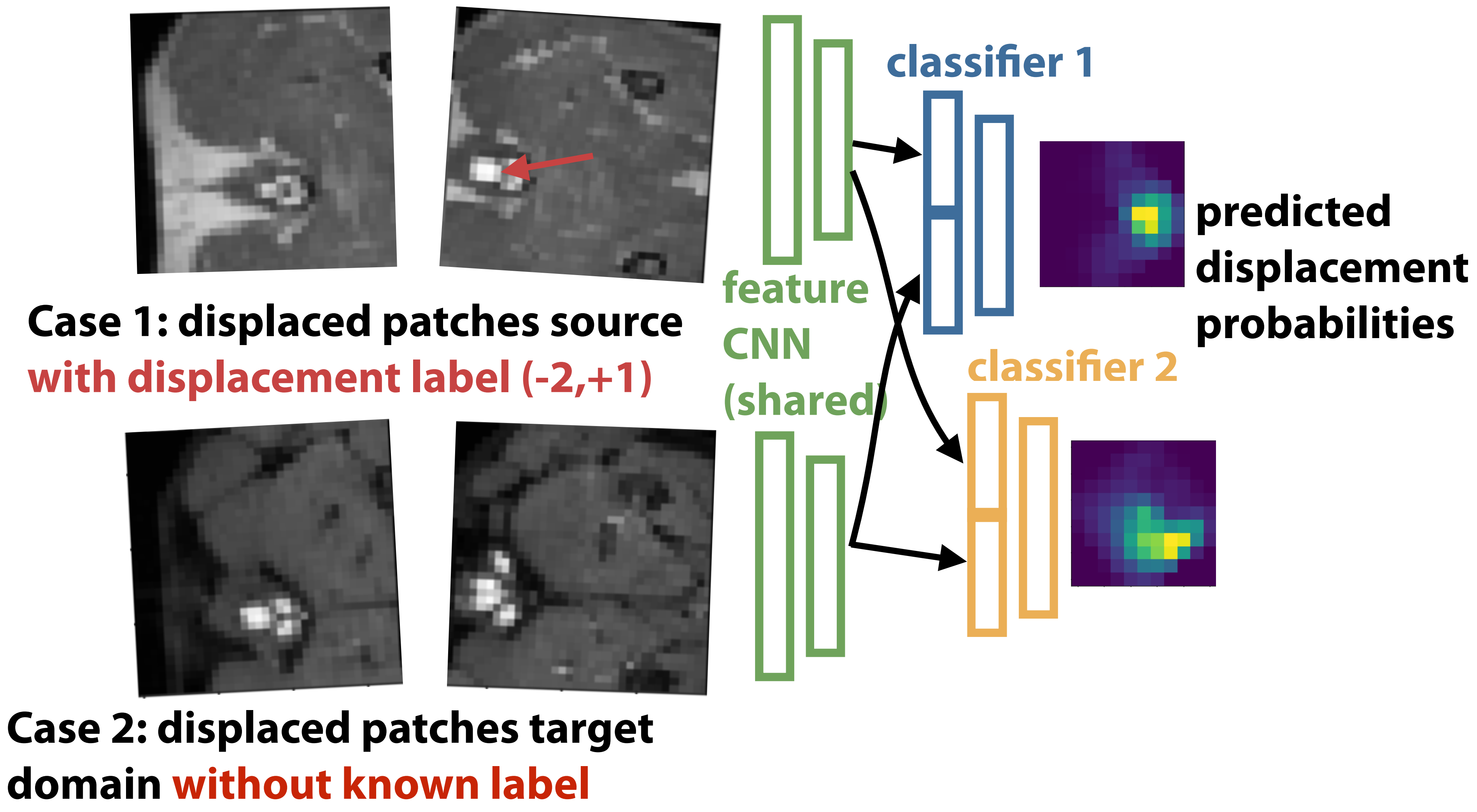
source domain with labels, target domain without
two differently initialised classifiers, shared feature extractor
A) update both feature extractor & classifier: source supervision
B) upd. **classifiers** to **maximise** classifier **discrepancy on target**
C) upd. **feature extractors** to **minimise discrepancy on target**
→ **shifts target distributions** into 'correct' decision boundaries

discrepancy measure is pivotal in steps B/C
sliced Wasserstein (SWD) state-of-the-art for Dirac-like softmax distributions, but it is permutation invariant → **not sensitive for spatial displacements in discrete registration**

Lee: Sliced Wasserstein Discrepancy for Unsupervised Domain Adaptation **CVPR 2019**



Projected Earth Mover's discrepancy for discrete displacements

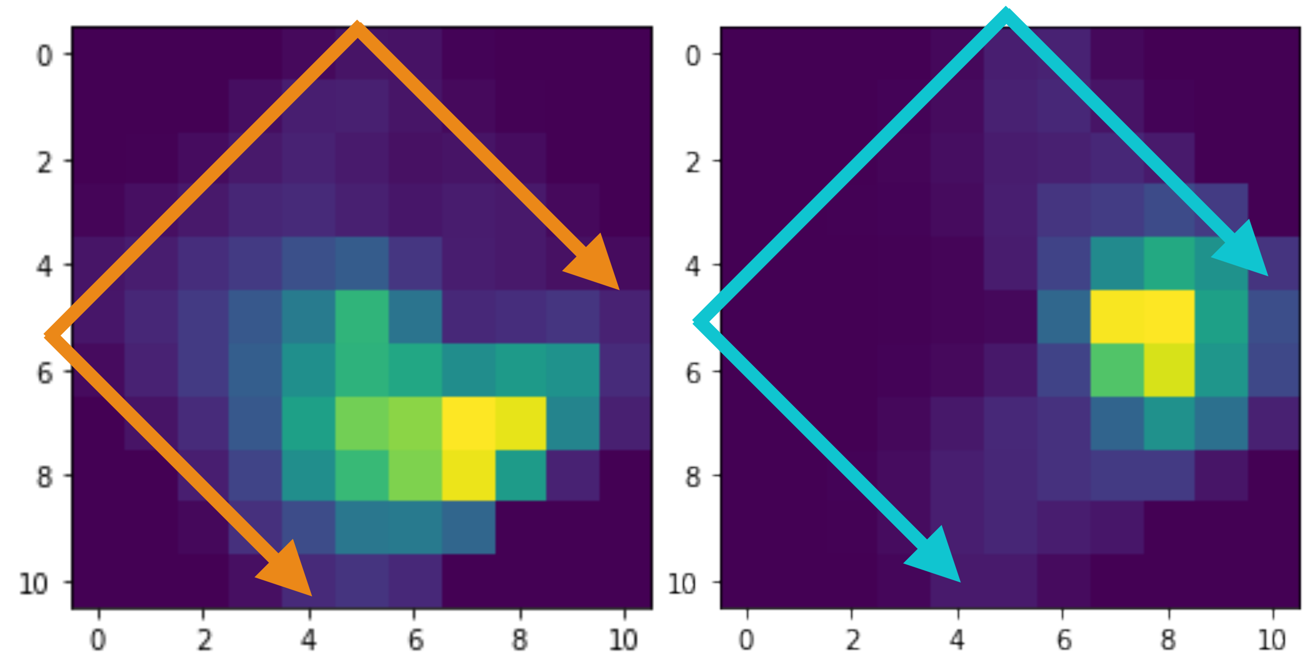


discrete patch-based registration *(25 displacement "classes")*
shared feature extractor - concatenation of fixed and moving
supervised with labels on T1 (source domain): **cross-entropy** loss
→ **unsupervised adaptation** of feature extractor and classifier **for new domain / modality** (T2, multi-contrast) **p-EMD discrepancy**
2D experiments on MICCAI SATA 2013 canine dataset
range of displacements: {−38, −19, 0, +19, +38}² pixels

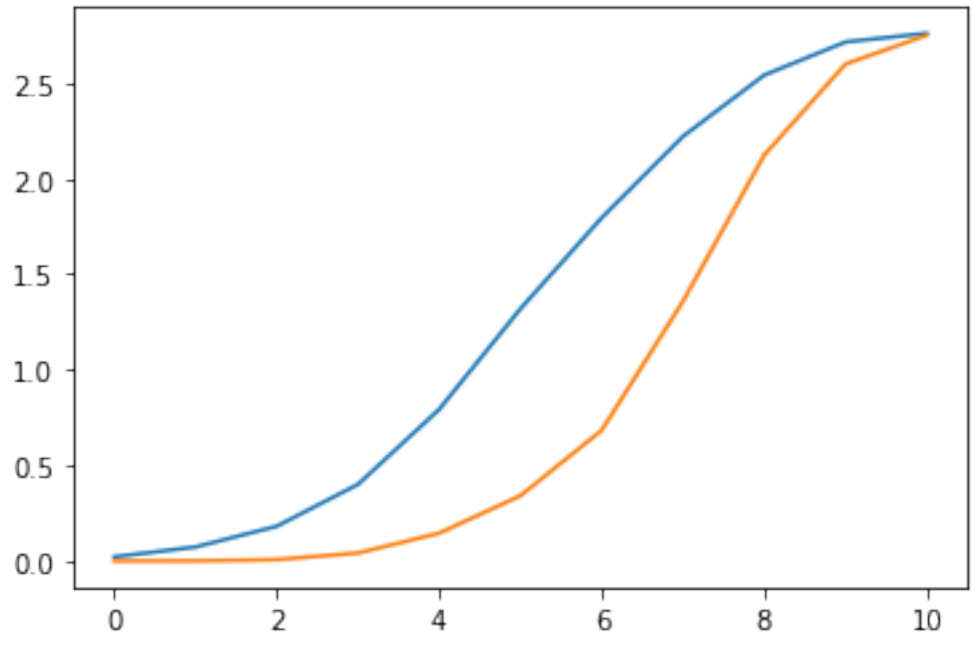
Earth Mover's distance (EMD) solves optimal transport problem, exact solution for 1D histograms exist
Our novel 2D (3D) approximation projects histograms onto 1D using multiple angles followed by cumulative histogram → discrepancy larger if peaks are spatially distant

Wermann: A Distance Metric for Multidimensional Histograms **CVGIP 1985**

project 2D to 1D along certain angles

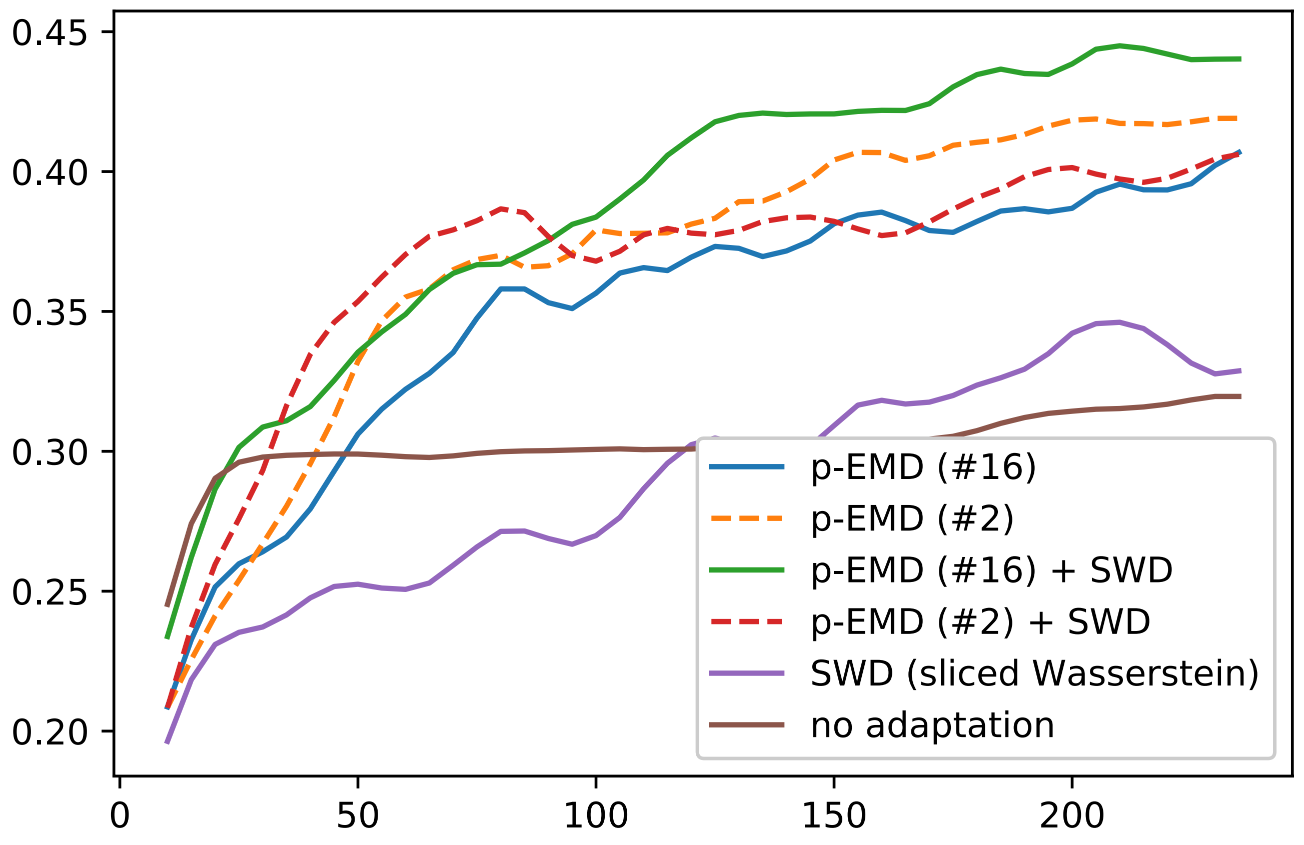


cumulative histogram

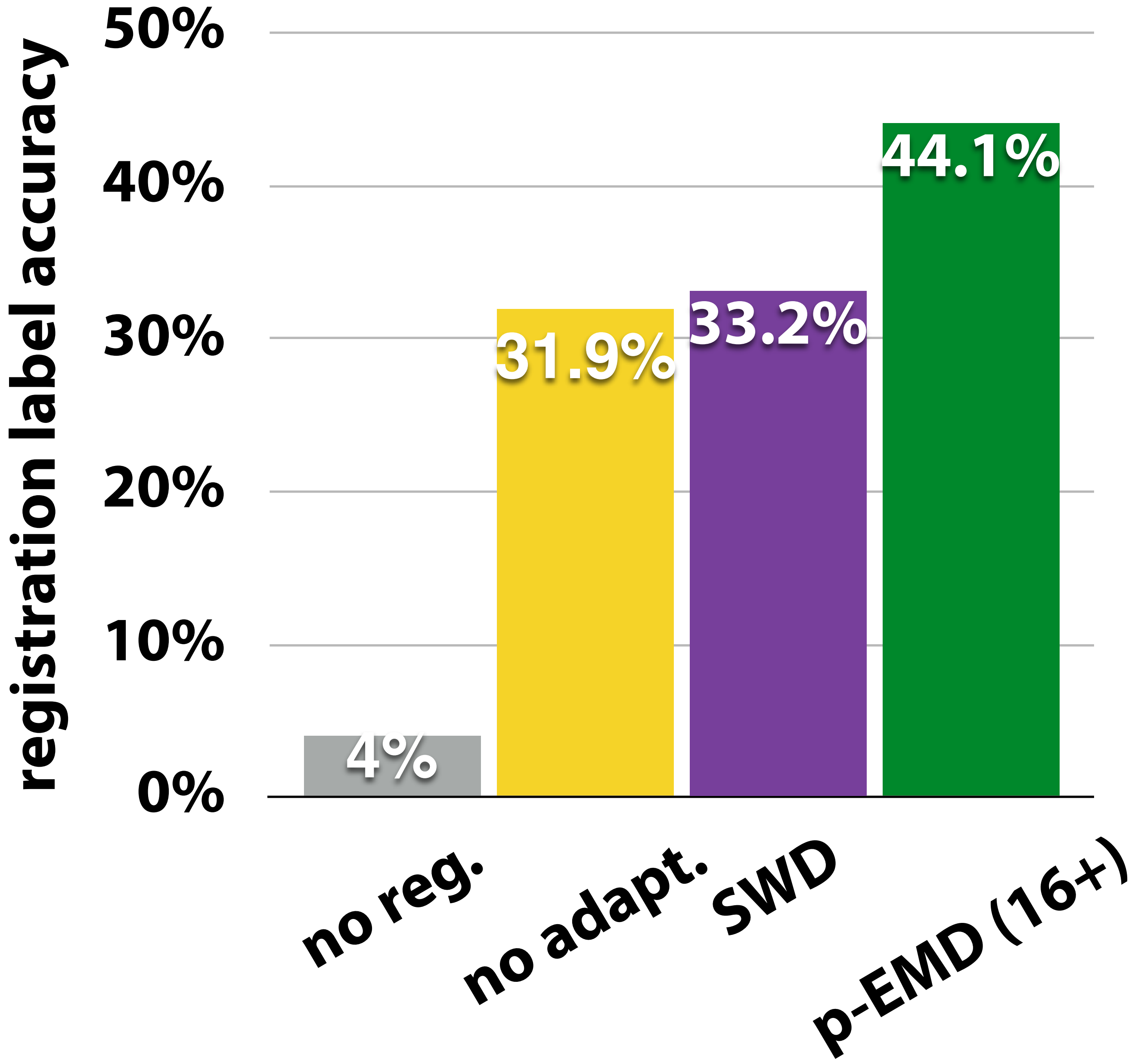


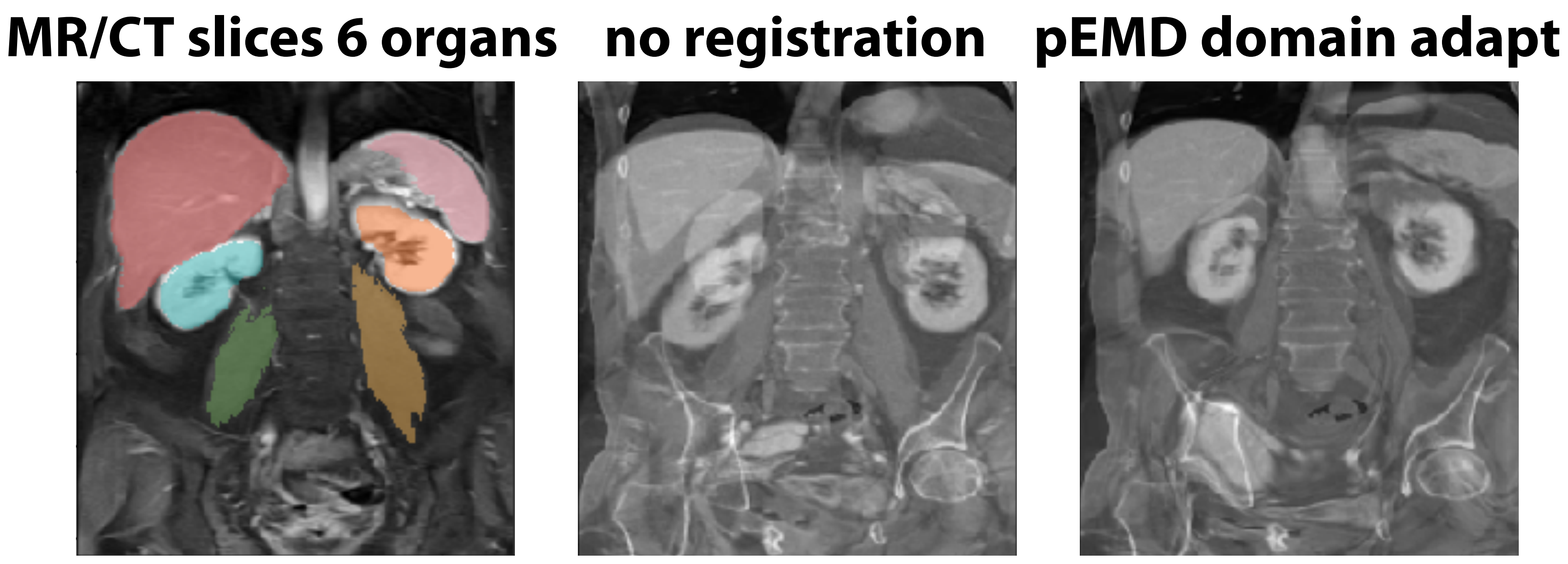
Initial experimental results and multimodal work-in-progress

tricks that help: scale prediction by 0.1 before softmax, supervised update only for classifier 1 with labels
combination of 16 projection p-EMD (0-90°) + sliced Wasserstein (SWD)) **outperforms state-of-the-art (SWD) by 11%**



experimental validation (test accuracy over epochs)





test CT/MR	no reg	train MR/ MR	train MR/ MR & CT/CT	multimodal domain adapt
Dice (6 labels)	**50.1%** ±19	**45.8%** ±23	**55.1%** ±21	**60.2%** ±18

paper: synthetic patch-based registration only MR T1/T2
four blocks of Conv2d, InstanceNorm and PReLU (13k weights)
➞ 18x18 feature map with 16 channels
concatenated for three block classification network (70k weights)
➞ prediction of 25D classification vector

new: fully deformable MR-CT (81 real registrations)
21x21 (441) displacement labels, graphical model regularisation and instance optimisation as post-processing, ➞ Heinrich Closing the gap.. **MICCAI 2019**
dataset ➞ Blendowski Learning .. multi-modal feat. **MIDL 2019**