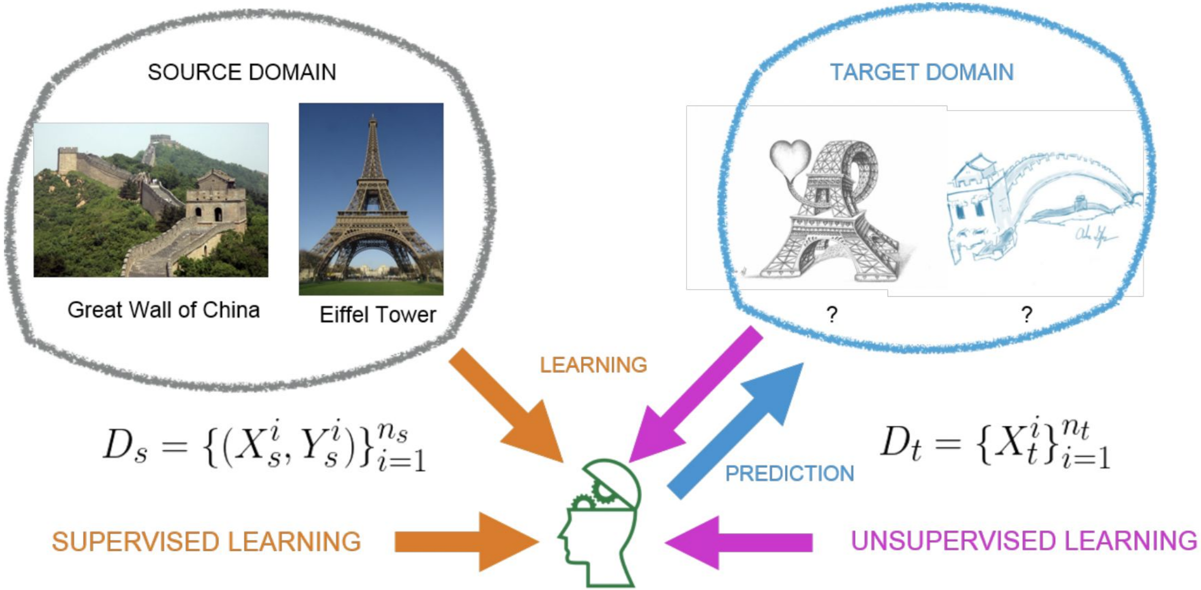
MNIST-UDA - Unsupervised Domain Adaptation

Presented by Yash (ys4yh)

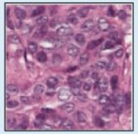
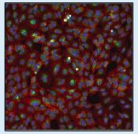
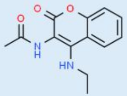
What is Domain Adaptation (DA)?

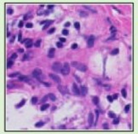
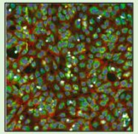
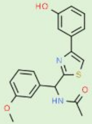


Leveraging **labeled source domain**, to learn a model for the **target domain.**

Different Scenarios

	Dataset	iWildCam	Camelyon17	RxRx1	FMoW	PovertyMap	GlobalWheat	OGB-MolPCBA	CivilComments	Amazon	Py150
	Input (x)	camera trap photo	tissue slide	cell image	satellite image	satellite image	wheat image	molecular graph	online comment	product review	code
	Prediction (y)	animal species	tumor	perturbed gene	land use	asset wealth	wheat head bbox	bioassays	toxicity	sentiment	autocomplete
	Domain (d)	camera	hospital	batch	time, region	country, ru/ur	location, time	scaffold	demographic	user	git repo

	Source example								What do Black and LGBT people have to do with bicycle licensing?	Overall a solid package that has a good quality of construction for the price.	`import numpy as np`
											…
											`norm=np.___`

	Target example								As a Christian, I will not be patronizing any of those businesses.	I *loved* my French press, it's so perfect and came with all this fun stuff!	`import subprocess as sp`
											`p=sp.Popen()`
											`stdout=p.___`

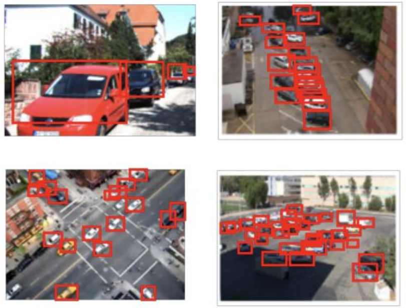
	Original paper	Beery et al. 2020	Bandi et al. 2018	Taylor et al. 2019	Christie et al. 2018	Yeh et al. 2020	David et al. 2021	Hu et al. 2020	Borkan et al. 2019	Ni et al. 2019	Raychev et al. 2016
Labeled	# domains	323	5	51	16 x 5	23 x 2	47	120,084	16	3,920	8,421
	# examples	203,029	455,954	125,510	141,696	19,669	6,515	437,929	448,000	539,502	150,000

Reference: Koh, Pang Wei, et al. "Wilds: A benchmark of in-the-wild distribution shifts." International Conference on Machine Learning. PMLR, 2021.

Visual DA Scenarios

Recognition

Detection



Segmentation

Re-identification

Control

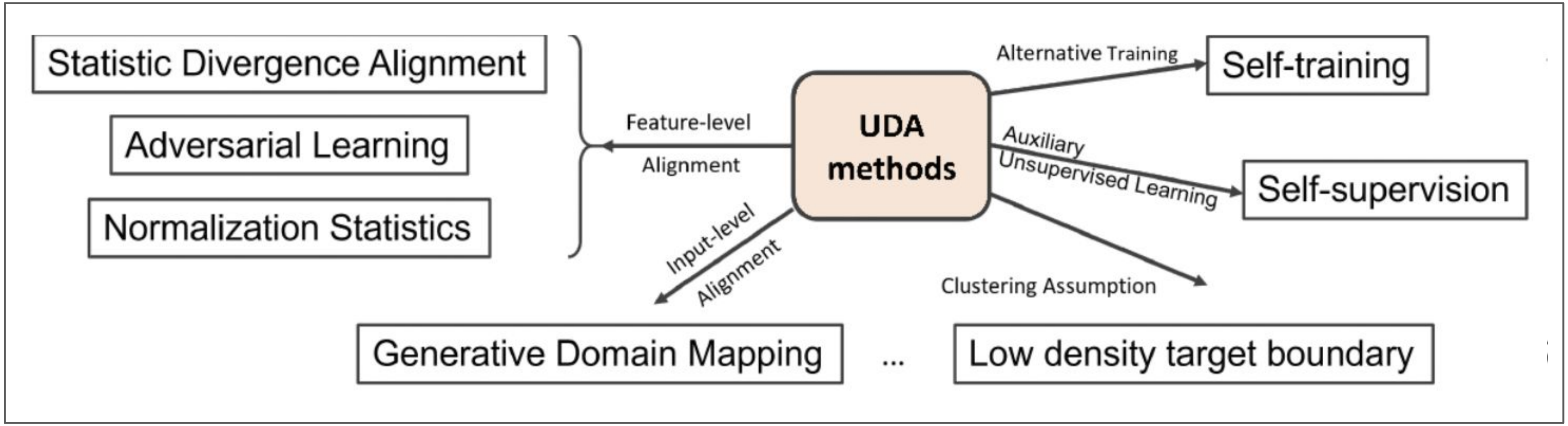
Visual localization

Different type of Shifts

Covariate Shift $p_s(x) \neq p_t(x)$	Label Shift $p_s(y) \neq p_t(y)$
Conditional Shift $p_s(x\|y) \neq p_t(x\|y)$	Concept Shift $p_s(y\|x) \neq p_t(y\|x)$

Reference: Liu, Xiaofeng, et al. "Deep unsupervised domain adaptation: A review of recent advances and perspectives." APSIPA Transactions on Signal and Information Processing 11.1 (2022)

Recent Approaches



Popular Methods

- Maximum-Mean Discrepancy
- Contrastive Domain Discrepancy
- Domain Adversarial NN
- Adaptive Batch Normalization
- GANs

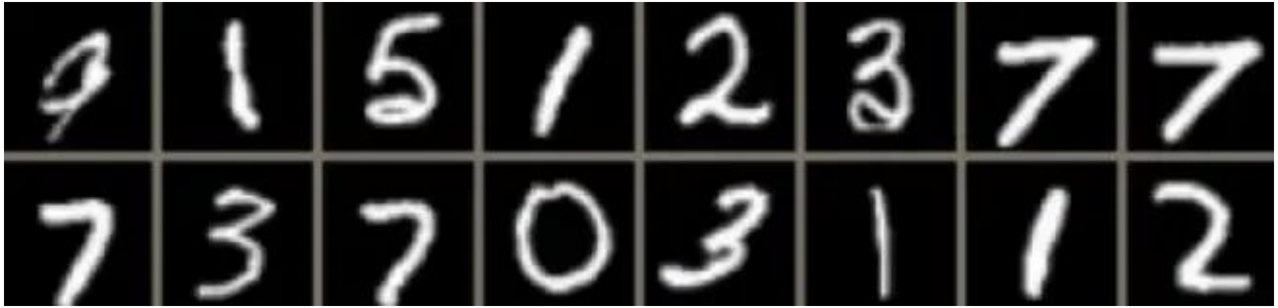
- Pseudo-labels
- Pretext learning
- Entropy minimization
- Consistency Regularization

Reference: Liu, Xiaofeng, et al. "Deep unsupervised domain adaptation: A review of recent advances and perspectives." APSIPA Transactions on Signal and Information Processing 11.1 (2022)

Our Problem Set-Up

Source Domain
MNIST Data

(60K Labeled Training Images & 10K Validation Images)



Target Domain
MNIST-M Data
= MNIST + BSDS500

(60K Unlabeled Training Images & 10K Testing Images)

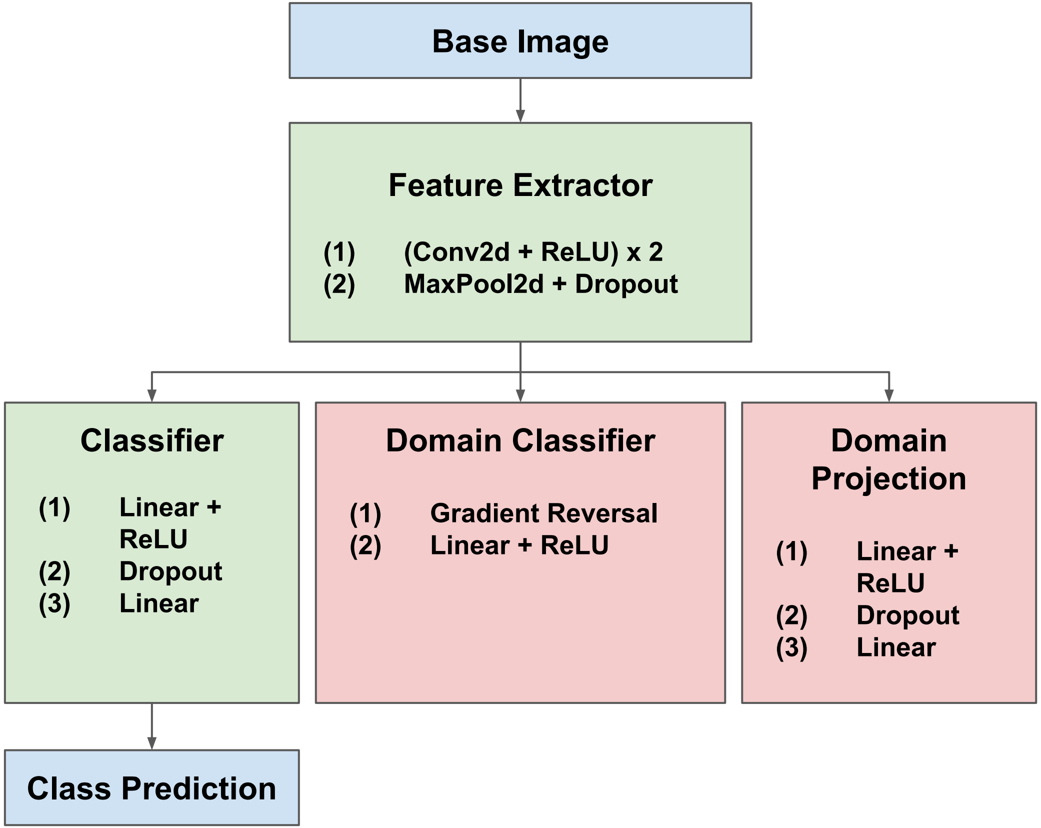
Baseline Approach

Approach:

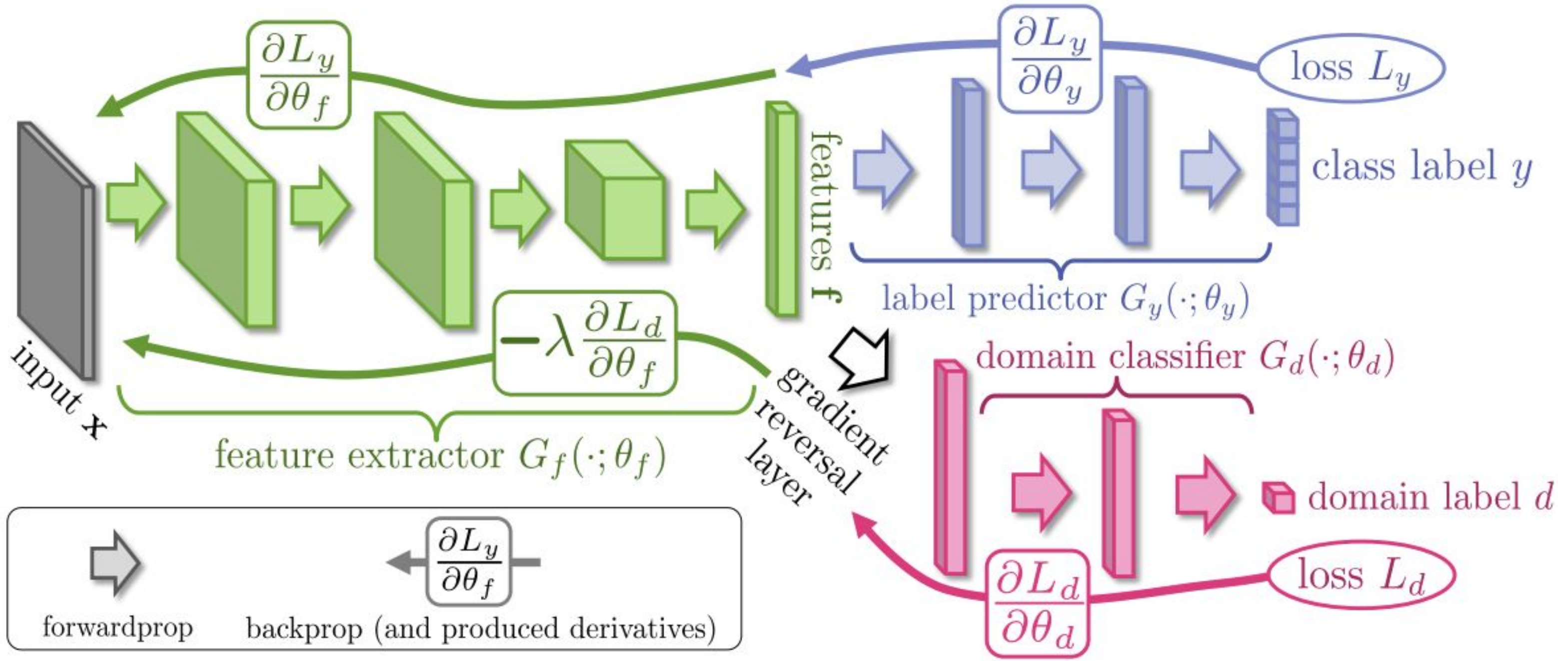
- Training on **MNIST** Data
  - 20 Epochs
  - Adam Optimizer
  - Learning Rate = 1e-3
  - Cross Entropy Loss

- Testing on **MNIST-M** Data

Testing Accuracy = 53%



Unsupervised Domain Adaptation by Backpropagation



Reference: Ganin, Yaroslav, and V. Lempitsky. "Unsupervised domain adaptation by backpropagation. arXiv." arXiv preprint arXiv:1409.7495 (2014).

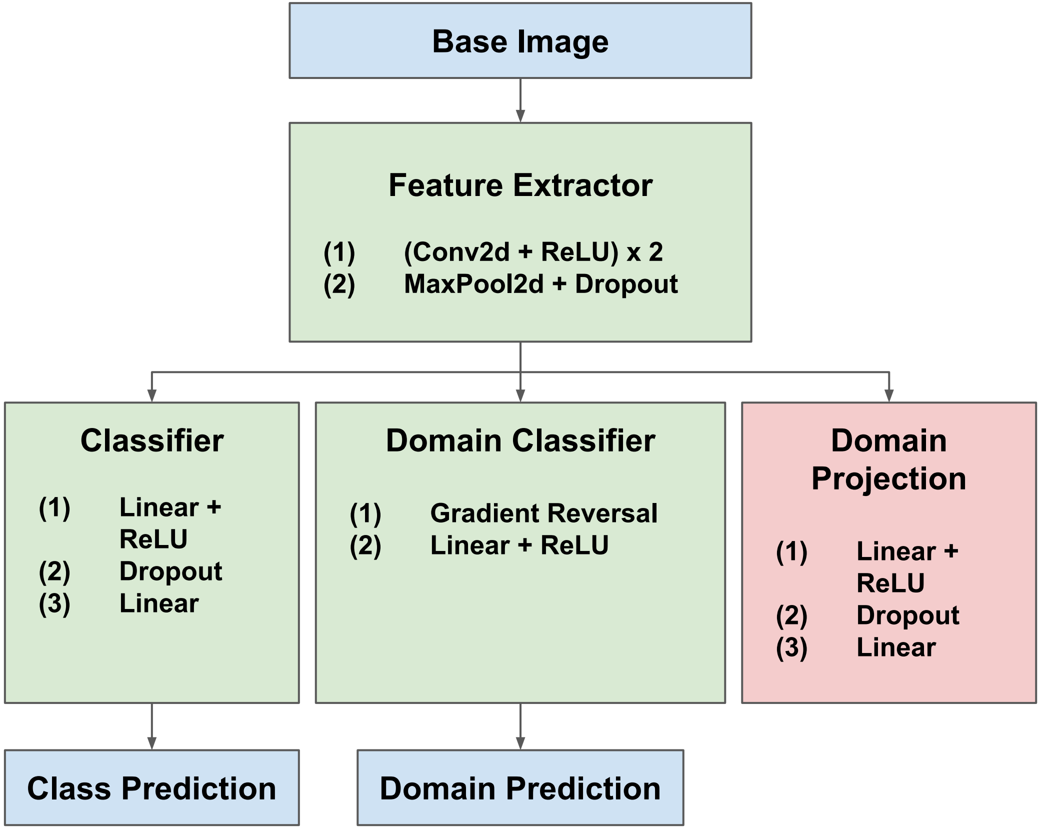
DAN Approach

Approach:

- Training on labeled **MNIST data** and unlabeled **MNIST-M data**
  - 40 Epochs
  - Adam Optimizer
  - Learning Rate = 1e-3
  - Cross Entropy Loss for Classifier
  - Binary Cross Entropy Loss for Domain Classifier

- Testing on **MNIST-M** Data

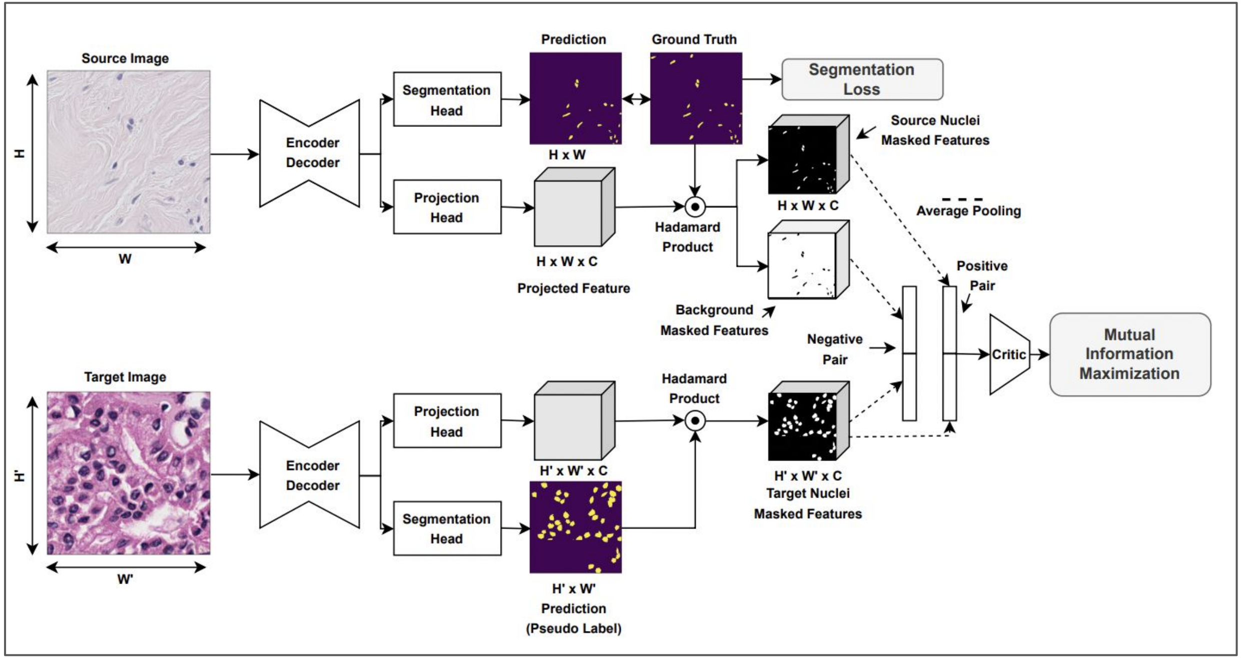
Testing Accuracy = 71%



MaNi: Maximizing Mutual Information for Nuclei Cross-Domain Unsupervised Segmentation

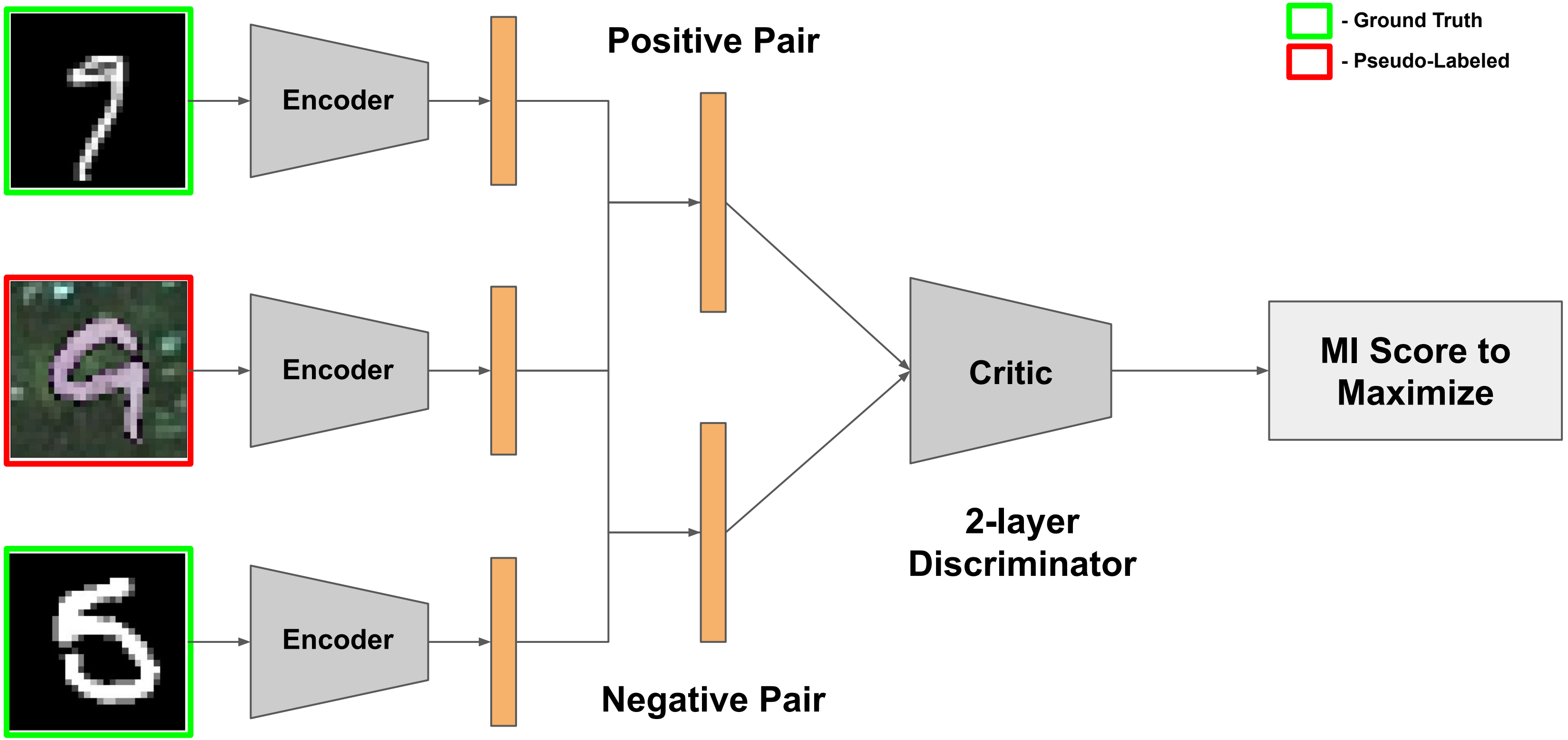
Proposed a **Jensen-Shannon divergence based Mutual Information loss** for **Unsupervised Domain Adaptation.**

Demonstrated strong performance for **Nuclei Semantic** Segmentation and **Instance** Segmentation with different architecture - **UNet** and **HoverNet** and for different cancer-type **domain shifts.**



Reference: Sharma, Yash, Sana Syed, and Donald E. Brown. "MaNi: Maximizing Mutual Information for Nuclei Cross-Domain Unsupervised Segmentation." International Conference on Medical Image Computing and Computer-Assisted Intervention. Springer, Cham, 2022.

Mutual Information Branch

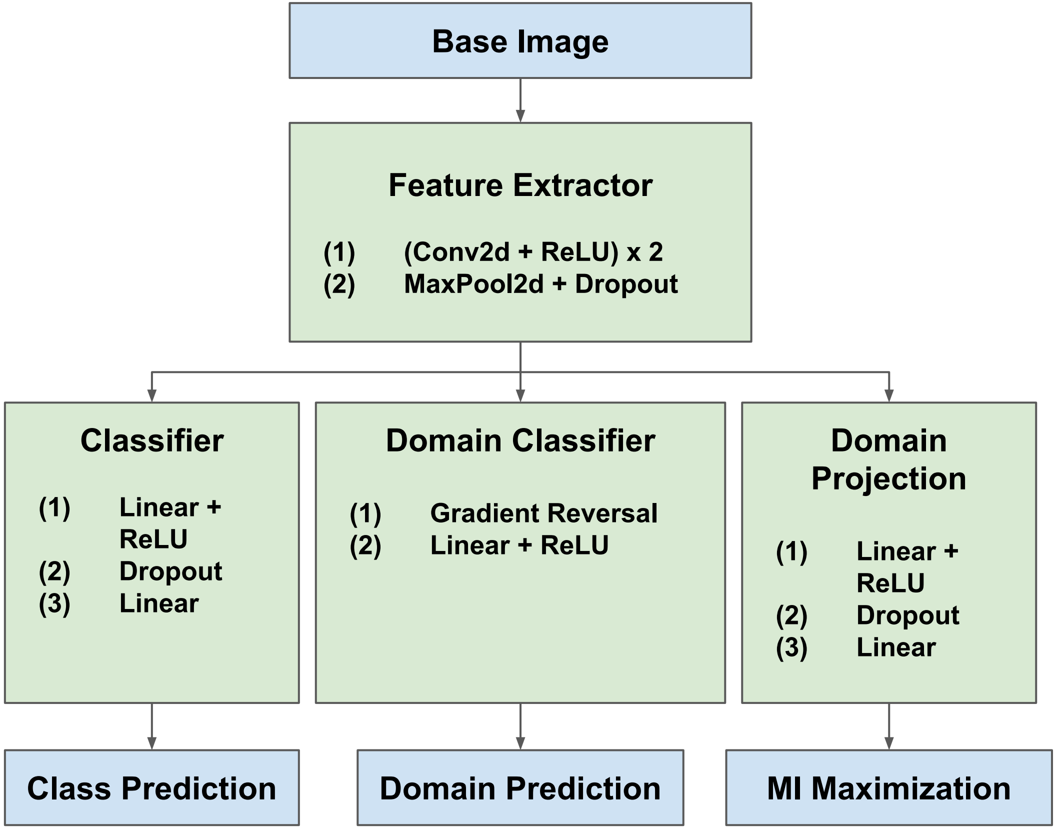


MI Maximization Approach

Approach:

- Training on labeled **MNIST data** and unlabeled **MNIST-M data**
  - 40 Epochs
  - Adam Optimizer
  - Learning Rate = 1e-3
  - Cross Entropy Loss for Classifier
  - Binary Cross Entropy Loss for Domain Classifier
- Fine-Tune further for 40 epochs by including Mutual Information loss.
- Testing on **MNIST-M** Data

Testing Accuracy = 87%



Thank you! Any questions?

References:

1. Domain Adaptation for Visual Applications, ECCV 2020 Tutorial
2. Koh, Pang Wei, et al. "Wilds: A benchmark of in-the-wild distribution shifts." International Conference on Machine Learning. PMLR, 2021.
3. Liu, Xiaofeng, et al. "Deep unsupervised domain adaptation: A review of recent advances and perspectives." APSIPA Transactions on Signal and Information Processing 11.1 (2022)
4. Ganin, Yaroslav, and V. Lempitsky. "Unsupervised domain adaptation by backpropagation. arXiv." arXiv preprint arXiv:1409.7495 (2014).
5. Sharma, Yash, Sana Syed, and Donald E. Brown. "MaNi: Maximizing Mutual Information for Nuclei Cross-Domain Unsupervised Segmentation." International Conference on Medical Image Computing and Computer-Assisted Intervention. Springer, Cham, 2022.