BOSTON UNIVERSITY

Domain Adversarial Training

Team 9

Marvin Martin & Anirudh Mandahr

CS523 Deep Learning - 2021

Plan

- ➢ Introduction
- ➢ Datasets
- ➢ Deep Convolutional Neural Network
- ➢ Domain Adversarial Neural Network
- ➢ Multi-Adversarial Domain Adaptation
- ➢ Experiments
- ➢ Results
- ➢ Difficulties
- ➢ Conclusion
- ➢ References

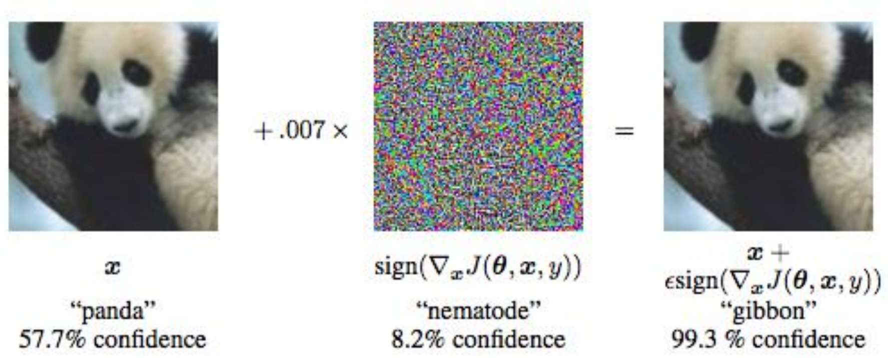
Introduction

Problem Statement:

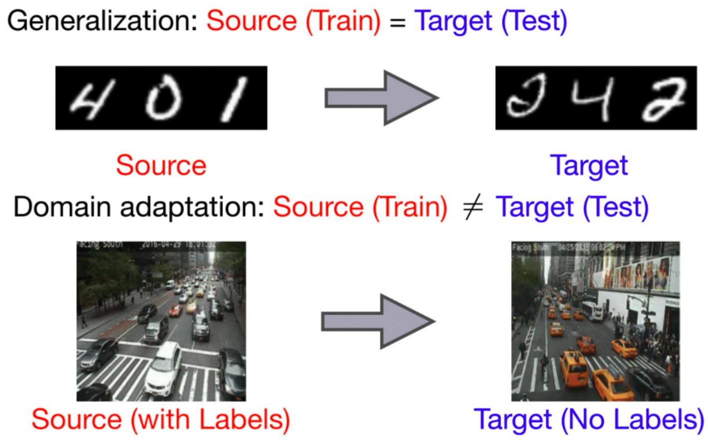
Deep convolutional neural network tends to be **weak at generalizing** on any type of image distribution and are therefore very depends on their training dataset distribution. This **lack of robustness** makes CNN easily fooled by adversarial examples.

The goal of **Adversarial Training** is to force a model to be less sensitivity to adversarial examples and therefore be **more robust**. One very interesting adversarial training is relative to domain distribution. In the real world, we often want to **adapt from a source domain labeled dataset** to different **target domain unlabeled datasets**.

Adversarial Example [1]



Domain Adaptation



Datasets

MNIST [2]

MNIST-M [3]

Both MNIST and MNIST-M

- 10 Classes
- (28x28x3)
- 50,000 Training examples
- 10,000 Validation examples
- 10,000 Test examples

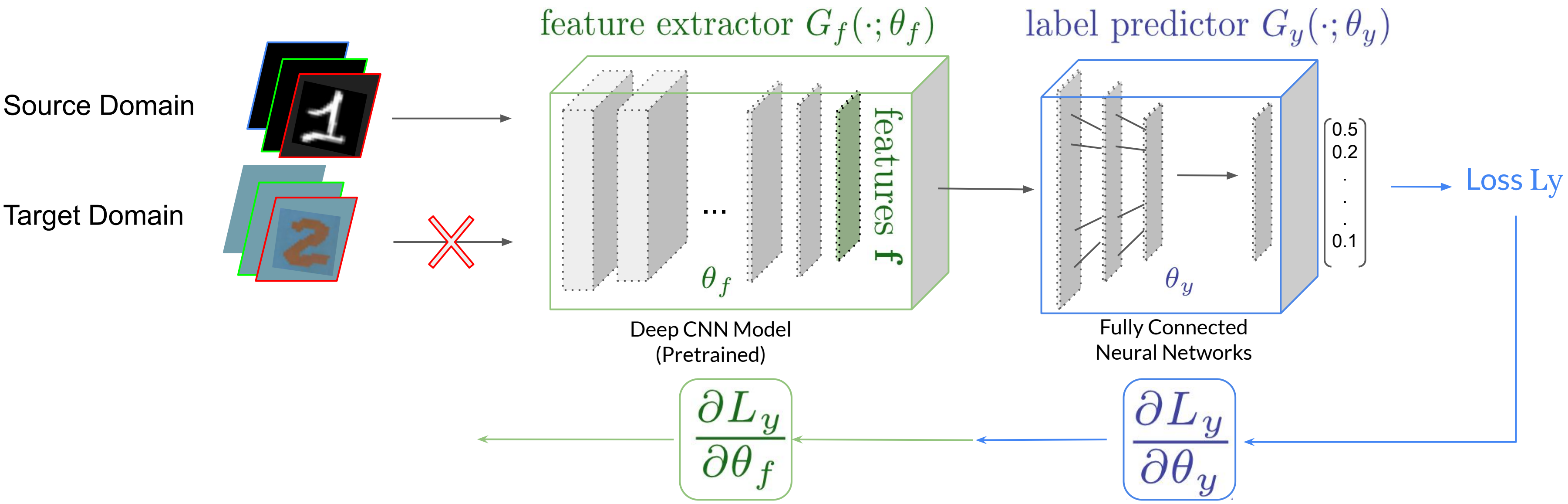
OFFICE-31 [4]

- 31 Classes
- Train 80%, Val 10%, Test 10%
- Amazon - 2,817 examples ($300 \times 300 \times 3$)
- DSLR - 498 examples($1000 \times 1000 \times 3$)
- Webcam - 795 examples (423×423x3)

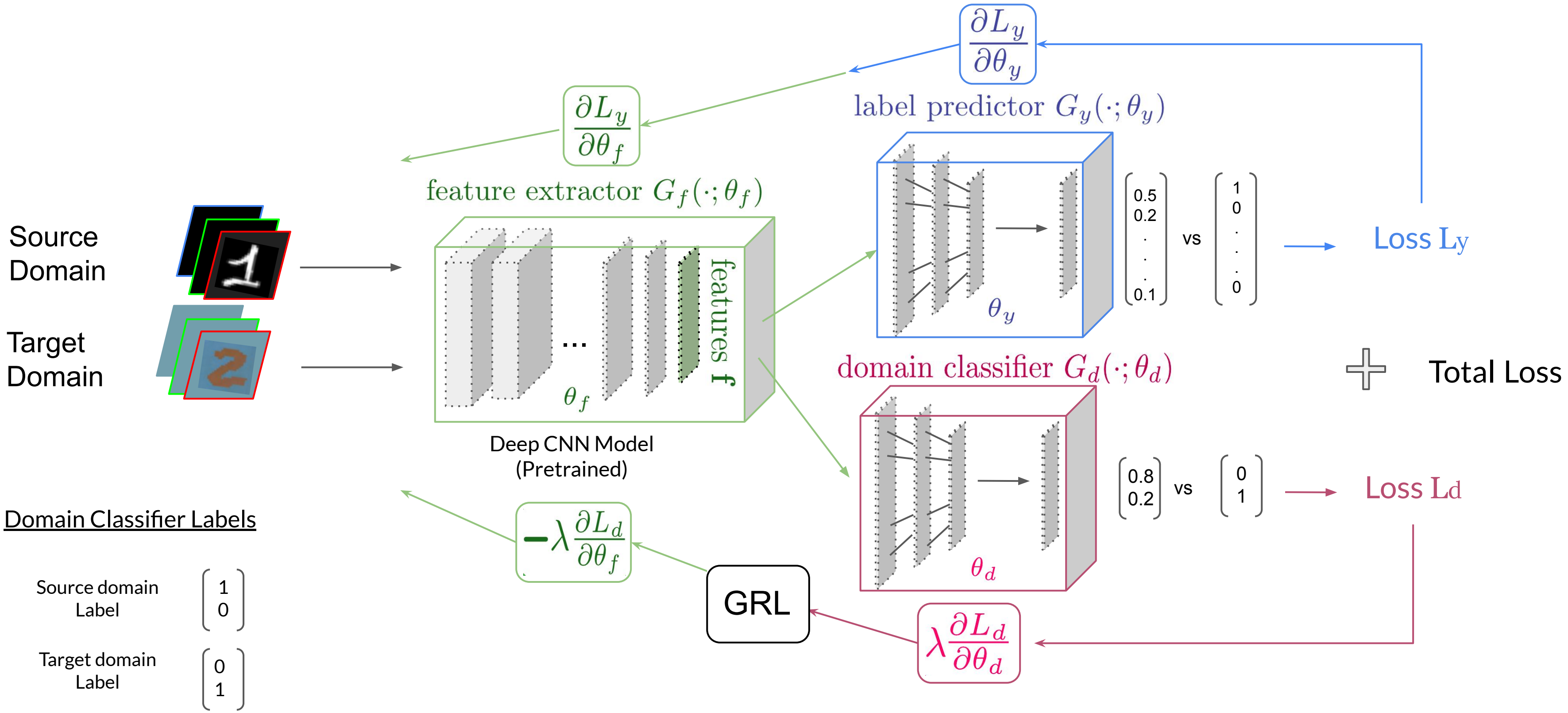
Deep Convolutional Neural Network

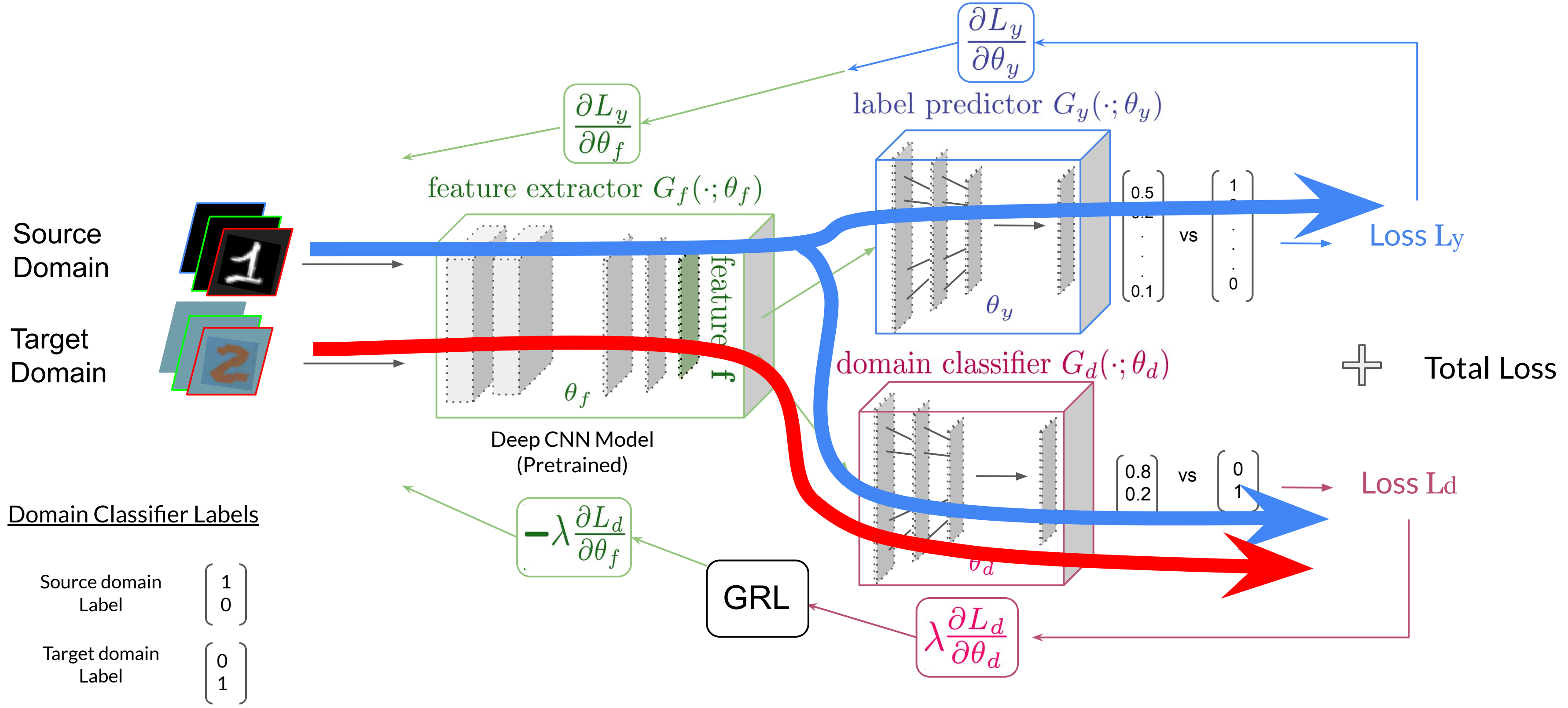
- Uses Transfer Learning [5]
- Only trained on Source dataset
- Evaluate at test time on Target dataset

- Feature f will not learn the target representation
- This DCNN will not perform well on any other domain distribution than its source
- Model is not robust to adversarial examples



Domain Adaptation Neural Network [6]

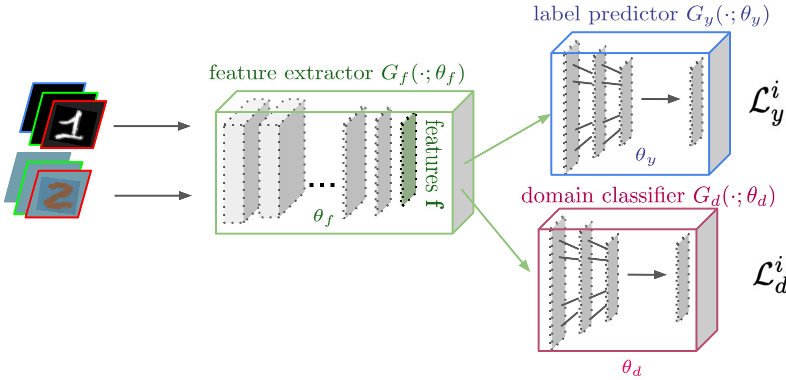




$\frac{\partial L_y}{\partial \theta_y}$
$\frac{\partial L_y}{\partial \theta_f}$
label predictor $G_y(\cdot;\theta_y)$
feature extractor $G_f(\cdot;\theta_f)$
Source Domain
Target Domain
feature f
θ_f
θ_y
0.5
0.1
vs
1
0
Loss Ly
Total Loss
domain classifier $G_d(\cdot;\theta_d)$
Deep CNN Model (Pretrained)
0.8
0.2
vs
0
1
Loss Ld
$-\lambda \frac{\partial L_d}{\partial \theta_f}$
GRL
$\lambda \frac{\partial L_d}{\partial \theta_d}$
θ_d
Domain Classifier Labels
Source domain Label
1
0
Target domain Label
0
1

$$S = \{(\mathbf{x}_i, y_i)\}_{i=1}^{n} \sim (\mathcal{D}_\mathrm{S})^n$$

$$T = \{\mathbf{x}_i\}_{i=n+1}^{N} \sim (\mathcal{D}_\mathrm{T}^X)^{n'}$$



$$\mathcal{L}_y^i(\theta_f, \theta_y) = \mathcal{L}_y\big(G_y(G_f(\mathbf{x}_i;\theta_f);\theta_y), y_i\big)$$

$$\mathcal{L}_d^i(\theta_f, \theta_d) = \mathcal{L}_d\big(G_d(G_f(\mathbf{x}_i;\theta_f);\theta_d), d_i\big)$$

Source label predictor Loss

Source domain Loss

Target domain Loss

$$E(\theta_f, \theta_y, \theta_d) = \boxed{\frac{1}{n}\sum_{i=1}^{n} \mathcal{L}_y^i(\theta_f, \theta_y)} - \lambda\left(\boxed{\frac{1}{n}\sum_{i=1}^{n} \mathcal{L}_d^i(\theta_f, \theta_d)} + \boxed{\frac{1}{n'}\sum_{i=n+1}^{N} \mathcal{L}_d^i(\theta_f, \theta_d)}\right)$$

GRL

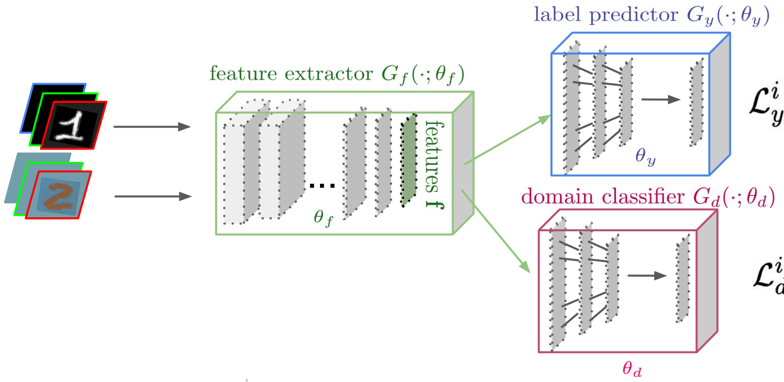
$$\boxed{\mathcal{R}(\mathbf{x}) = \mathbf{x}, \quad \frac{d\mathcal{R}}{d\mathbf{x}} = -\mathbf{I},}$$

$$\tilde{E}(\theta_f, \theta_y, \theta_d) = \boxed{\frac{1}{n}\sum_{i=1}^{n} \mathcal{L}_y\left(G_y(G_f(\mathbf{x}_i;\theta_f);\theta_y), y_i\right)}$$

$$- \lambda\left(\boxed{\frac{1}{n}\sum_{i=1}^{n} \mathcal{L}_d\left(G_d(\boxed{\mathcal{R}(G_f(\mathbf{x}_i;\theta_f))};\theta_d), d_i\right)} + \boxed{\frac{1}{n'}\sum_{i=n+1}^{N} \mathcal{L}_d\left(G_d(\boxed{\mathcal{R}(G_f(\mathbf{x}_i;\theta_f))};\theta_d), d_i\right)}\right).$$

$$S = \{(\mathbf{x}_i, y_i)\}_{i=1}^{n} \sim (\mathcal{D}_S)^n$$

$$T = \{\mathbf{x}_i\}_{i=n+1}^{N} \sim (\mathcal{D}_T^X)^{n'}$$



$$\mathcal{L}_y^i(\theta_f, \theta_y) = \mathcal{L}_y\big(G_y(G_f(\mathbf{x}_i;\theta_f);\theta_y), y_i\big)$$

$$\mathcal{L}_d^i(\theta_f, \theta_d) = \mathcal{L}_d\big(G_d(G_f(\mathbf{x}_i;\theta_f);\theta_d), d_i\big)$$

$$(\hat{\theta}_f, \hat{\theta}_y) = \underset{\theta_f, \theta_y}{\operatorname{argmin}}\ E(\theta_f, \theta_y, \hat{\theta}_d)$$

$$\hat{\theta}_d = \underset{\theta_d}{\operatorname{argmax}}\ E(\hat{\theta}_f, \hat{\theta}_y, \theta_d)$$

The goal is to learn $\boxed{\hat{\theta}_f \text{ (CNN)}}$, so that the feature f extracted is domain invariant, and therefore $\boxed{G_d(G_f(\mathbf{x}_i;\theta_f);\theta_d)}$ is not able to distinguish the domains anymore (e.g maximize the Cost).

$$\theta_f \longleftarrow \theta_f - \mu\left(\frac{\partial \mathcal{L}_y^i}{\partial \theta_f} - \lambda \frac{\partial \mathcal{L}_d^i}{\partial \theta_f}\right)$$

$$\theta_y \longleftarrow \theta_y - \mu \frac{\partial \mathcal{L}_y^i}{\partial \theta_y},$$

$$\theta_d \longleftarrow \theta_d - \mu\lambda \frac{\partial \mathcal{L}_d^i}{\partial \theta_d},$$

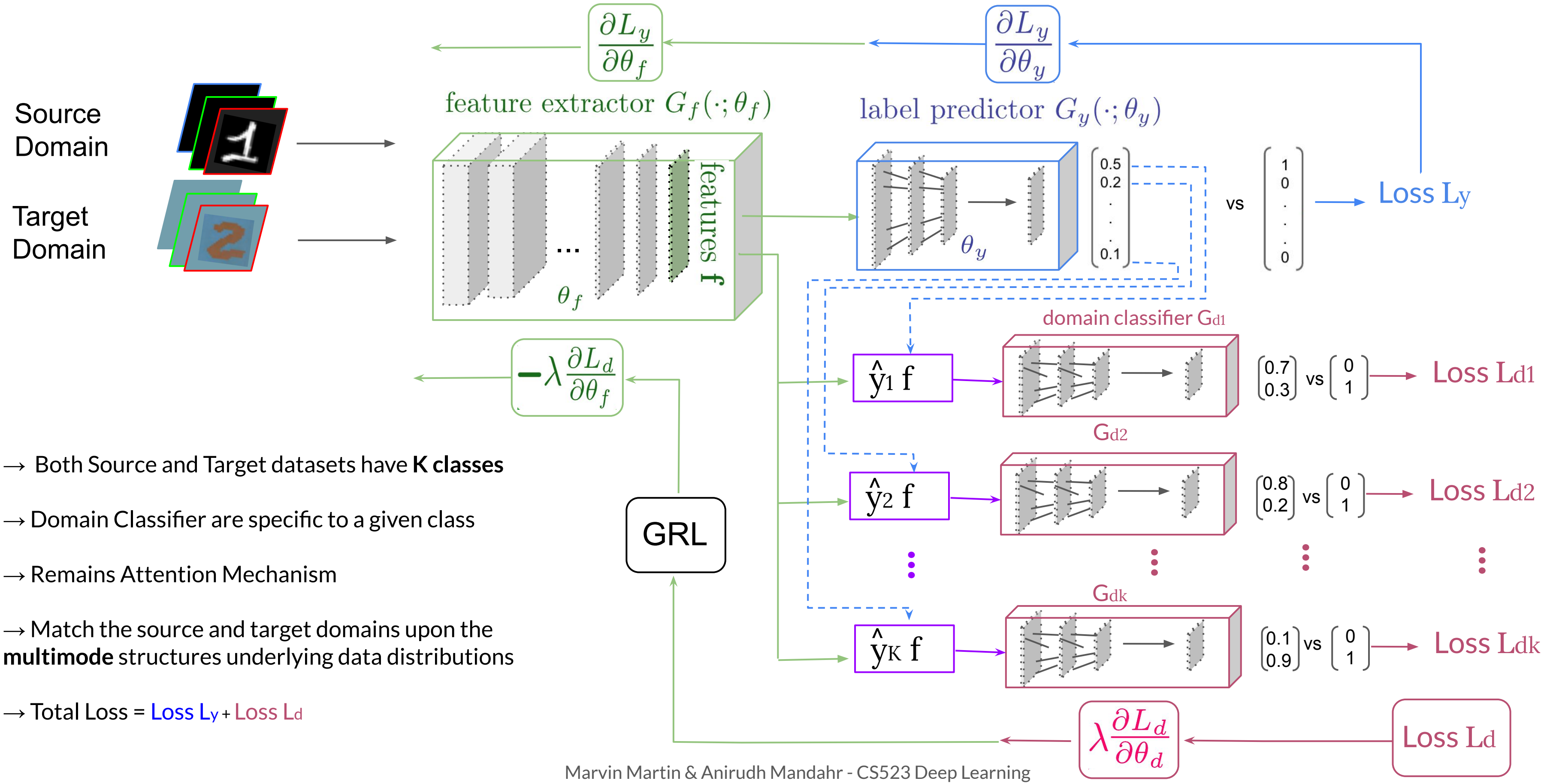
- Learning Rate:

$$\mu_p = \frac{\mu_0}{(1 + \alpha \cdot p)^{\beta}},$$

- Lambda:

$$\lambda_p = \frac{2}{1 + \exp(-\gamma \cdot p)} - 1$$

Multi-Adversarial Domain Adaptation [7]



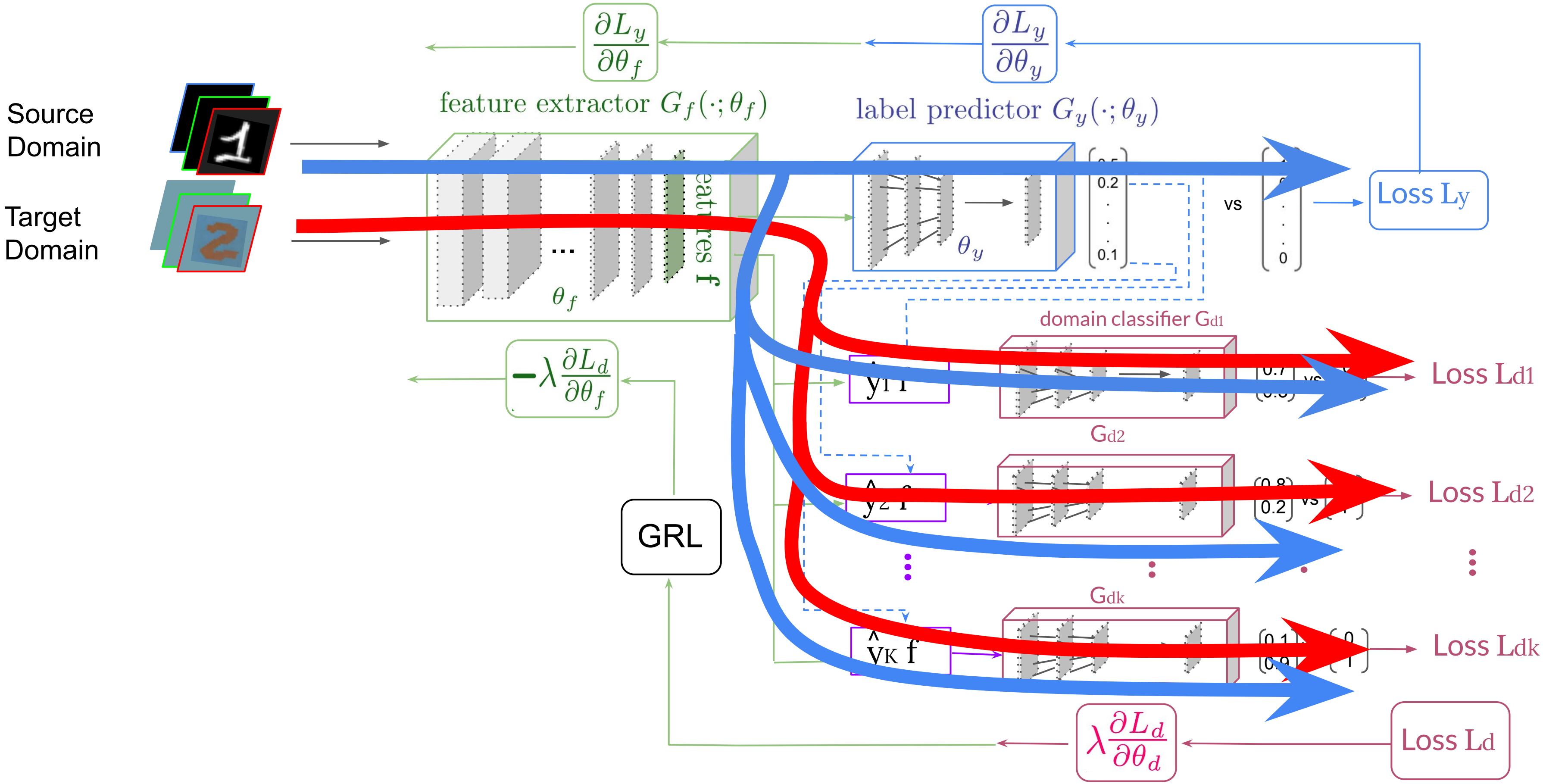
→ Both Source and Target datasets have **K classes**

→ Domain Classifier are specific to a given class

→ Remains Attention Mechanism

→ Match the source and target domains upon the **multimode** structures underlying data distributions

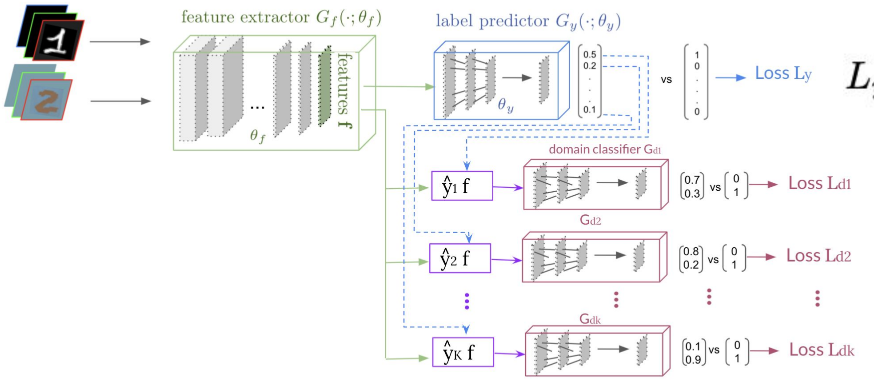
→ Total Loss = Loss L_y + Loss L_d



Source Domain
Target Domain
$\frac{\partial L_y}{\partial \theta_f}$
$\frac{\partial L_y}{\partial \theta_y}$
feature extractor $G_f(\cdot;\theta_f)$
label predictor $G_y(\cdot;\theta_y)$
θ_f
θ_y
0.2
0.1
vs
0
Loss Ly
domain classifier Gd1
$-\lambda\frac{\partial L_d}{\partial \theta_f}$
Loss Ld1
Gd2
0.2
Loss Ld2
GRL
Gdk
Loss Ldk
$\lambda\frac{\partial L_d}{\partial \theta_d}$
Loss Ld

$$\mathcal{D}_s = \{(\mathbf{x}_i^s, \mathbf{y}_i^s)\}_{i=1}^{n_s}$$

$$\mathcal{D}_t = \{\mathbf{x}_j^t\}_{j=1}^{n_t}$$



$$L_y\left(G_y\left(G_f\left(\mathbf{x}_i\right)\right), y_i\right)$$

$$\sum_{k=1}^{K} L_d^k\left(G_d^k\left(\hat{y}_i^k G_f\left(\mathbf{x}_i\right)\right), d_i\right)$$

$$C\left(\theta_f, \theta_y, \theta_d^k|_{k=1}^K\right) = \frac{1}{n_s} \boxed{\sum_{\mathbf{x}_i \in \mathcal{D}_s} L_y\left(G_y\left(G_f\left(\mathbf{x}_i\right)\right), y_i\right)} - \frac{\lambda}{n} \boxed{\sum_{k=1}^{K} \sum_{\mathbf{x}_i \in \mathcal{D}} L_d^k\left(G_d^k\left(\hat{y}_i^k G_f\left(\mathbf{x}_i\right)\right), d_i\right)}$$

$$(\hat{\theta}_f, \hat{\theta}_y) = \arg\min_{\theta_f, \theta_y} C\left(\theta_f, \theta_y, \theta_d^k|_{k=1}^K\right),$$

$$(\hat{\theta}_d^1, \ldots, \hat{\theta}_d^K) = \arg\max_{\theta_d^1, \ldots, \theta_d^K} C\left(\theta_f, \theta_y, \theta_d^k|_{k=1}^K\right)$$

Experiments

PyTorch Lightning [8]

PyTorch

Weights & Biases [9]

docker

NVIDIA

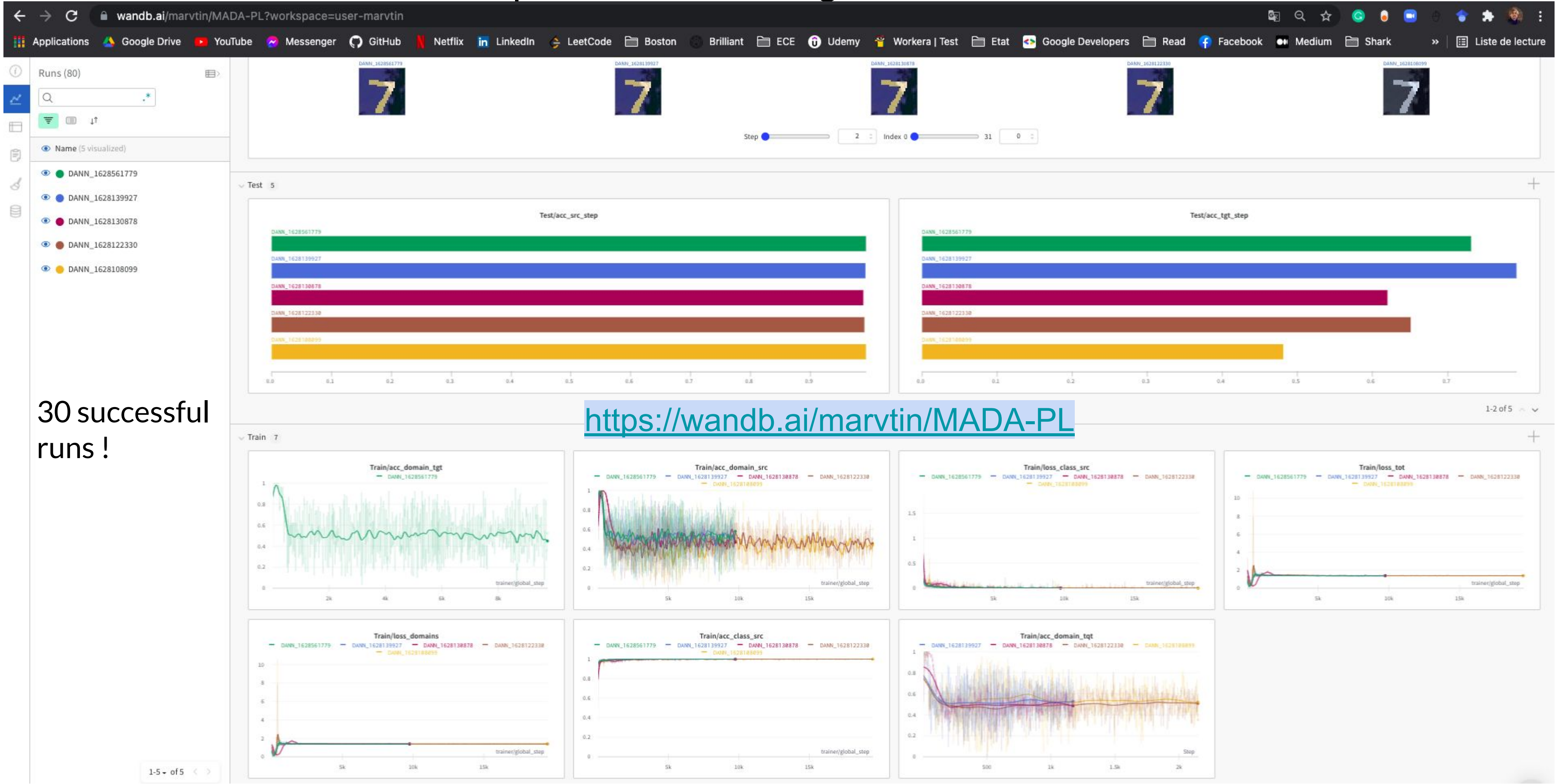
Experiment configuration files

config.yml

```yaml
input:
  dataset:
    src: "AMAZON" # Source Dataset name(MNIST or WEBCAM)
    tgts: ["DSLR"] # Target Datasets name, please do not provide several targets for MADA.
    transformation :
        img_size: 224 # size of input if images input
        src : transform_RGB_DA # name of the transform to perform on source data
        tgt : transform_RGB_DA # name of the transform to perform on target data
        mean: [0.485, 0.456, 0.406] # mean used for normalization (from resnet)
        std: [0.229, 0.224, 0.225] # std used for normalization (from resnet)

model:
  type : DANN # MADA, DANN
  backbone: resnet34 #resnet18, resnet34, resnet152
  pretrained_backbone: imagenet # if not imagenet then not pretrained
  n_layers_freeze: 0 # Depends on your backbone
  class_classifier: linear3_bn2_v1 # linear2_dr2_bn, linear2_bn, linear3_bn2_v1, linear3_bn2_v2
  domain_classifier: linear3_bn2_v2

training:
  gpus: 1
  num_workers: 0
  optimizer:
    type: Adam #Adam, SGD
    momentum: 0.9
    lr: 0.001
    weight_decay: 2.5e-5
  scheduler:
    lr_schedule: true
    alpha: 10
    gamma: 10
    beta: 0.75
  batch_size: 256
  epochs: 50

seed: 8888 #random seed for reproducibilty
```

Weights & Biases

Experiments Tracking and Iterations



30 successful runs !

https://wandb.ai/marvtin/MADA-PL

Experiment Run Example

Results

Classification accuracies between source and target domain for MNIST and OFFICE 31 Datasets

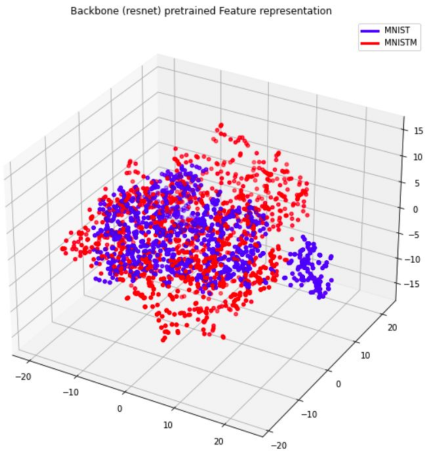
	MNIST → MNISTM		AMAZON → DSLR		AMAZON → WEBCAM	
	Test Source Accuracy	Test Target Accuracy	Test Source Accuracy	Test Target Accuracy	Test Source Accuracy	Test Target Accuracy
Our DCNN (Train on Source only)	.9916	.265 (.5225)	.660	.580 (.689)	.762	.600 (.684)
Our DANN (from Ganin, Lempitsky et al 2015)	.9918	**.7917** (.7666)	.760	.580 (.797)	.700	.600 (.820)
Our MADA (from Pei, Zhongyi, et al 2018)	.871	.3705	.740	.630 (.878)	.680	.650 (.90)
Our DCNN (Train on Target only)	.973 (.959)	.957	.360	.159	.987	.587

(*) from https://arxiv.org/pdf/1809.02176.pdf (MADA), https://arxiv.org/pdf/1505.07818v4.pdf (DANN).

*Feature extractor is ResNet18 /ResNet34/ResNet 152 fully retrained.
*Optimizer is SGD or Adam, Learning rate 0.001.
*FCNN are 2/3 dense layers followed by BatchNorm / Dropout.

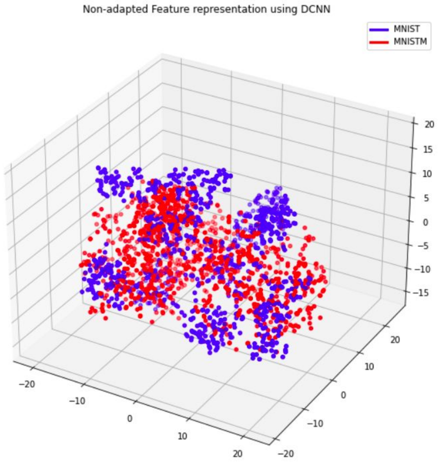
Top feature extractor visualisation using TSNE (MNIST and MNISTM Test Dataset)

RESNET18



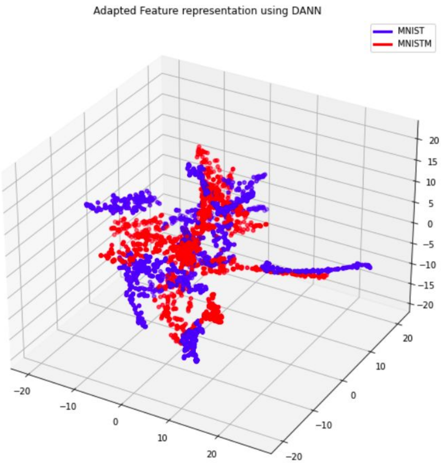
- Source: No cluster per class
- Target: No cluster per class
- Distribution separated

DCNN



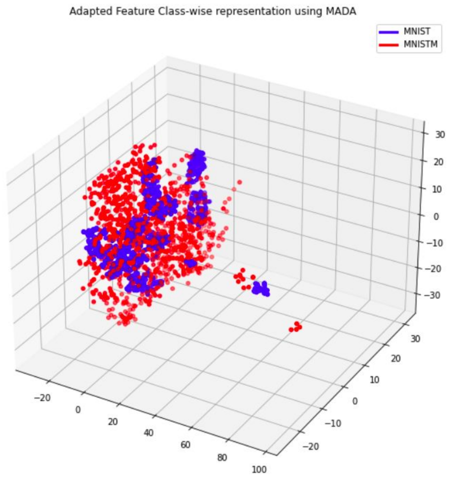
- Source: **clusters** per class
- Target: No cluster per class
- Distribution separated

DANN



- Source: **clusters** per class
- Target: **clusters** per class
- Distribution **Mixed**

MADA



- Source: **clusters** per class
- Target: No clusters per class
- Distribution mostly separated

Difficulties

- Unbalanced dataset repartition between Source and Target.
- Unstable Training between domain classifier and feature extractor.
- Requires more GPU Memory to load both Source and Target simultaneously.
- Optimizing using a single Optimizer (unlike GAN’s)
- MADA has only very few implementation on the web (only in C++ from the original paper)

Conclusion

What we have learned:

- Good practices for ML Project Experimentation
- Better read Deep Learning papers
- Implement only by looking the paper
- Research is difficult!

Future work:

- Try different batch loading techniques for MADA to fix the unbalanced issues
- Try to use 2 separate Optimizers for MADA
- Use different Pretrained Feature Extractors (VGG, Xception, ViT, …)
- Try MDANN (domain classifiers are learned for K multiple Domains)

References

[1] Stanford CS231 Lecture 16 | Adversarial Examples and Adversarial Training (Ian Goodfellow) https://www.youtube.com/watch?v=CIfsB_EYsVI&t=4367s

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[8] Falcon, W. "PyTorchLightning/pytorch-lightning." *Pytorch Lightning* (2021).

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Q&A

Thank you!