Looking Back at Labels: A Class based Domain Adaptation Technique

Vinod K. Kurmi
Dept. of Electrical Engineering

Vinay P. Namboodiri
Dept. of Computer Science Engineering

Indian Institute of Technology Kanpur
India

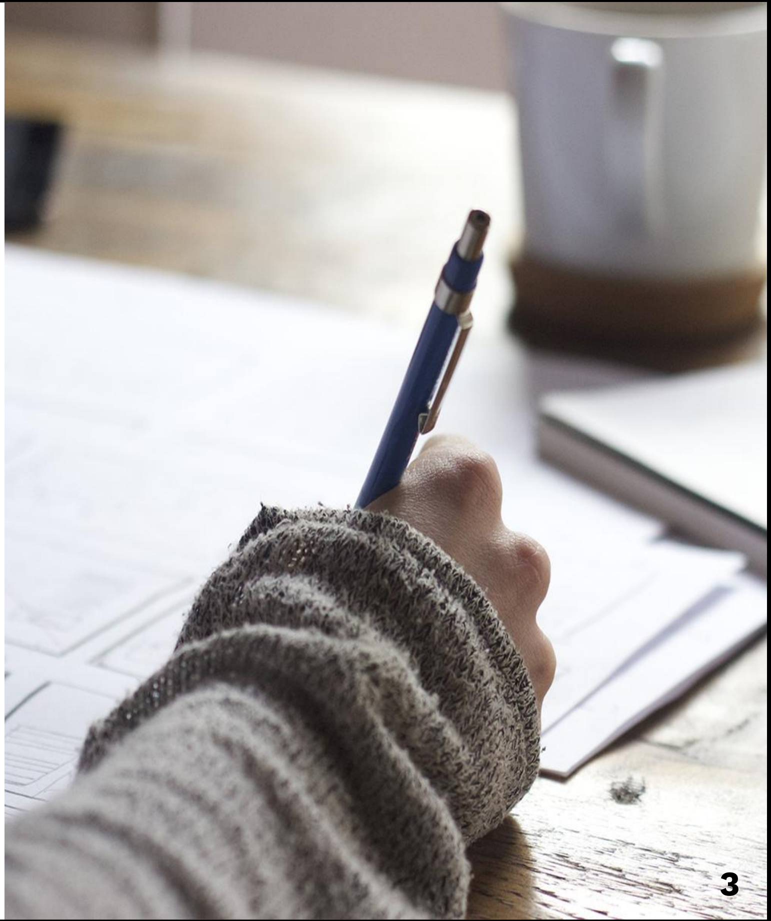
Outlines

- Introduction
- Motivation
- Problem Formulation
- Proposed Method
- Results and Discussion
- Conclusion

Introduction

Recent Successes of Deep Learning

- Object Recognition
- Object Detection
- Image Generation
- Visual Question Answer and Dialogue
- Image Segmentation
- Action Recognition
- ...
- ....
- .....
- ......

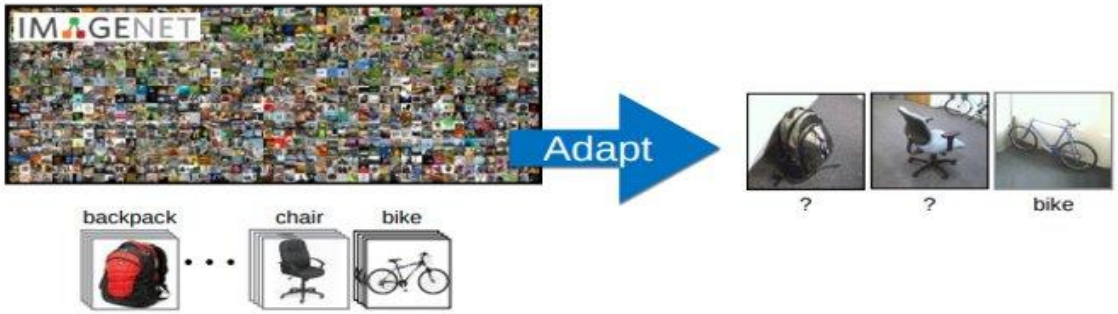


Motivation

Accuracy ~ 95%

Accuracy ~ 55%

Problem Formulation



Source Domain $\sim P_S(X, Y)$ $\neq$ Target Domain $\sim P_T(Z, H)$

lots of **labeled** data

unlabeled or limited labels

$$D_S = \{(\mathbf{x}_i, y_i), \forall i \in \{1, \ldots, N\}\}$$

$$D_T = \{(\mathbf{z}_j, ?), \forall j \in \{1, \ldots, M\}\}$$

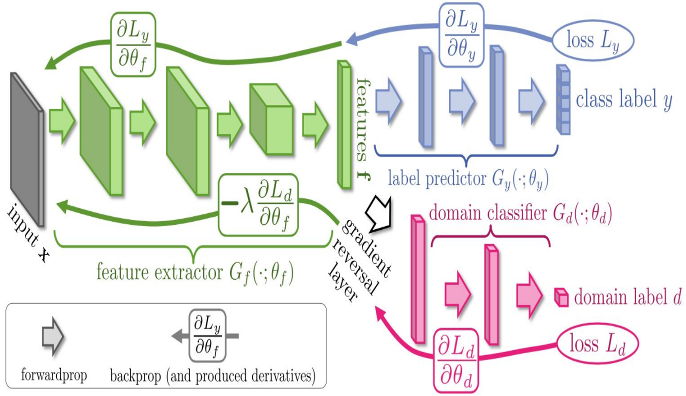
Slide credit: Kate Saenko

Related Work

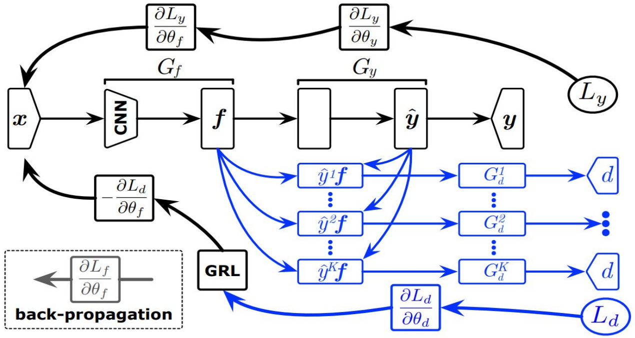
Adversarial Learning based Domain Adaptation

Related Work

Deep Adversarial Domain Adaptation (DAN)



Multi Adversarial Domain Adaptation(MADA)



Issues with Adversarial DA methods

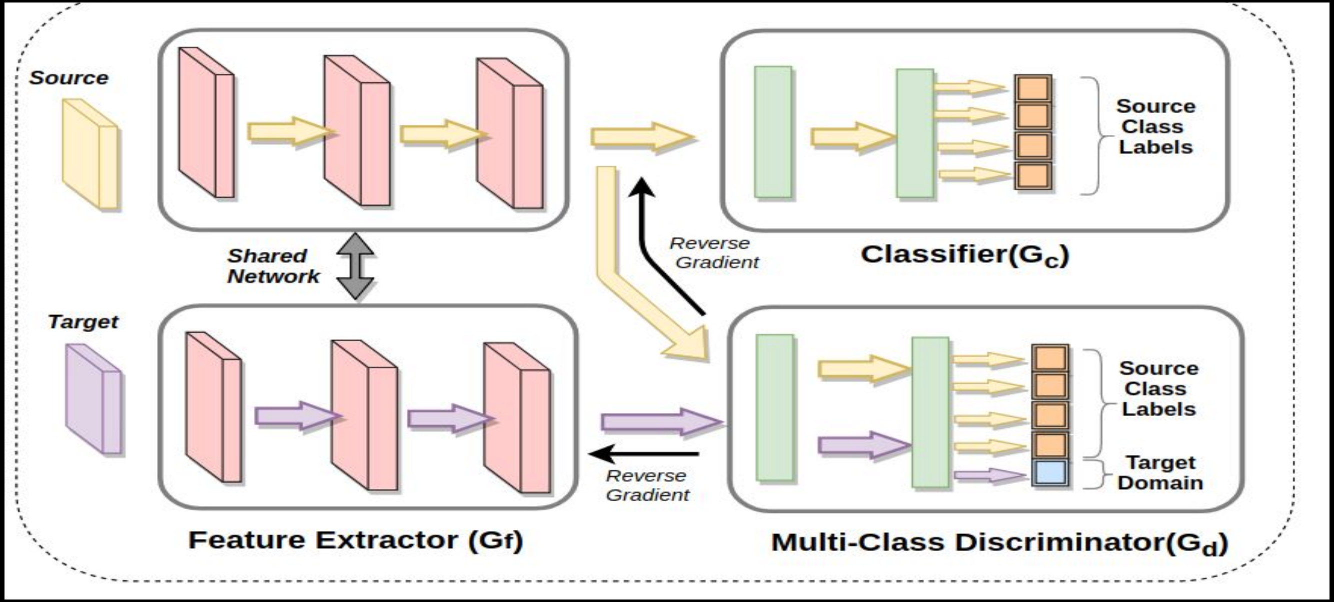
- **Mode Collapse**
- **Mis Alignment**
- **Dependencies on Source Classifier**
- **Complex Models**

Can be make discriminator more informative about data??

Can be make discriminator more informative about data??

- ***Avail the source label structure to discriminator***

Proposed Model



Why this ‘Informed Discriminator’ works??

For Target Samples:

Discriminator classify a target data sample to only one of the source class label. 👍

For Source Samples:

Discriminator classify all the source data sample to a single class(target class). ☹

 but source classifier ensures the inter class variance for source examples. ☻

Loss Function

$$loss(\theta_f, \theta_y, \theta_d) = \frac{1}{n_s} \sum_{x_i \in D_s} L_y(G_y(G_f(x_i)), y_i) + \frac{\lambda}{n} \sum_{x_i \in D_s \cup D_t} L_d(G_d(G_f(x_i)), d_i)$$

where

$$d_i = \begin{cases} y_i, & \text{if } x_i \in D_s. \\ |C| + 1, & \text{if } x_i \in D_t \ . \end{cases}$$

Results

Office -31 Dataset

Method	A → W	D → W	W → D	A → D	D → A	W → A	Avg
DDC	61.0 ± 0.5	95.0 ± 0.3	98.5 ± 0.3	64.9 ± 0.4	47.2 ± 0.5	49.4 ± 0.4	69.3
DAN	68.5 ± 0.3	96.0 ± 0.1	99.0 ± 0.1	66.8 ± 0.2	50.0 ± 0.4	49.8 ± 0.3	71.6
DeepCoral	66.4 ± 0.4	95.7 ± 0.3	99.2 ± 0.1	66.8 ± 0.6	52.8 ± 0.2	51.5 ± 0.3	72.0
WDAN	66.9 ± 0.2	95.9 ± 0.2	99.0 ± 0.1	64.4 ± 0.2	53.8 ± 0.1	52.7 ± 0.2	72.1
DHN	68.3 ± 0.0	96.1 ± 0.0	98.8 ± 0.0	66.4 ± 0.0	55.5 ± 0.0	53.0 ± 0.0	73.0
DRCN	68.7 ± 0.3	96.4 ± 0.3	99.0 ± 0.2	66.8 ± 0.5	56.0 ± 0.5	54.9 ± 05	73.6
RTN	73.3 ± 0.2	96.8 ± 0.2	99.6 ± 0.1	71.0 ± 0.2	50.5 ± 0.3	51.0 ± 0.1	73.7
GRL	73.0 ± 0.5	96.4 ± 0.3	99.2 ± 0.3	72.3 ± 0.3	52.4 ± 0.4	50.4 ± 0.5	73.9
I2I	75.3 ± 0.0	96.5 ± 0.0	99.6 ± 0.0	71.1 ± 0.0	50.1 ± 0.0	52.1 ± 0.0	74.1
JAN	75.2 ± 0.4	96.6 ± 0.2	99.6 ± 0.1	72.8 ± 0.3	57.5 ± 0.2	56.3 ± 0.2	76.3
CDAN	77.9 ± 0.3	96.9 ± 0.2	100.0 ± 0.0	74.6 ± 0.2	55.1 ± 0.3	57.5 ± 0.4	77.0
ADIAL	75.5 ± 0.0	96.6 ± 0.0	99.5 ± 0.0	73.6 ± 0.0	**58.1 ± 0.0**	**59.4 ± 0.0**	77.1
MADA	78.5 ± 0.2	99.8 ± 0.1	100.0 ± 0.0	74.1 ± 0.1	56.0 ± 0.2	54.5 ± 0.3	77.1
IDDA[ours]	**82.2 ± 0.8**	**99.8 ± 0.2**	**100.0 ± 0.0**	**82.4 ± 0.5**	54.1 ± 0.4	52.5 ± 0.3	**78.5**

Results

ImageClef Dataset

Method	I→P	P→I	I→C	C→I	C→P	P→C	Avg
AlexNet	66.2	70.0	84.3	71.3	59.3	84.5	73.9
DAN	67.3	80.5	87.7	76.0	61.6	88.4	76.9
GRL	66.5	81.8	89.0	79.8	63.5	88.7	78.2
RTN	67.4	82.3	89.5	78.0	63.0	90.1	78.4
MADA	68.3	**83.0**	91.0	80.7	63.8	92.2	79.8
IDDA	**68.3**	81.8	**92.3**	**81.6**	**67.2**	**92.8**	**80.6**

Does Source Label Hierarchy works ??

Mini Caltech- Bing Dataset

Total Images: 4960(Caltech) and 20731(Bing)

Parent Classes : 3

Aquatic, Terrestrial and Avian

Child Classes: 43 Classes

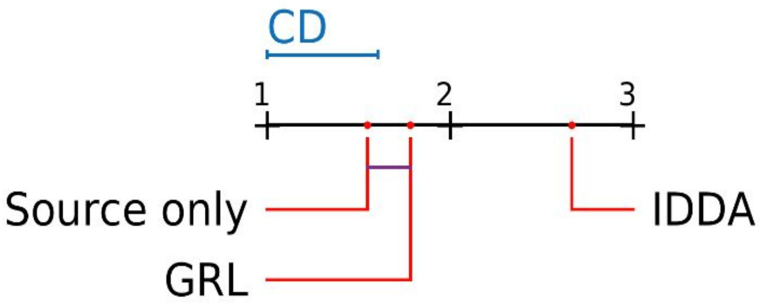
Aquatic (11 classes), Terrestrial (23 classes) and Avian (9 classes).

Results

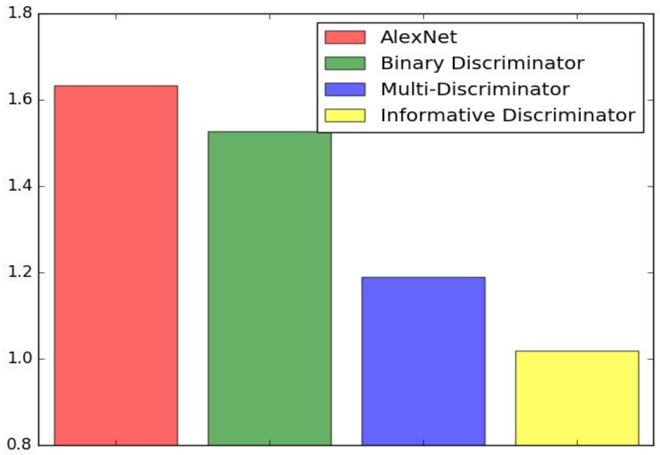
Method	C → B	B → C	M → M-M
Source Only	36.16	72.67	52.25
Binary Discriminator	36.35	73.29	76.66
Parent Label Discriminator[our]	36.50	73.87	-
Class Label Discriminator(IDDA)[ours]	**36.98**	**74.62**	**82.29**

Analysis

Statistical Significance Analysis

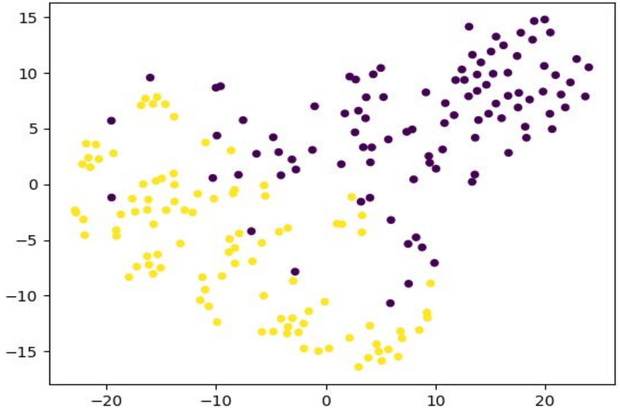


Proxy A Distance

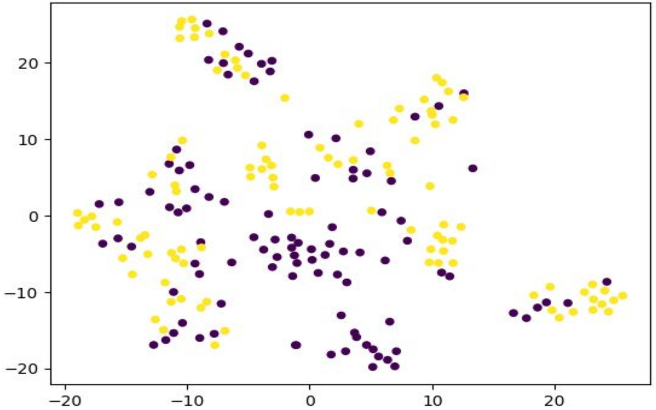


Feature Visualization

Before Adaptation



After Adaptation



Conclusion

- We proposed a method for obtaining an informative discriminator that aids improved domain adaptation.

- The incorporation of structure in source and correlating that with the target structure is a promising direction which we have initiated through this work

Thanks!

Special thanks to..

Questions!

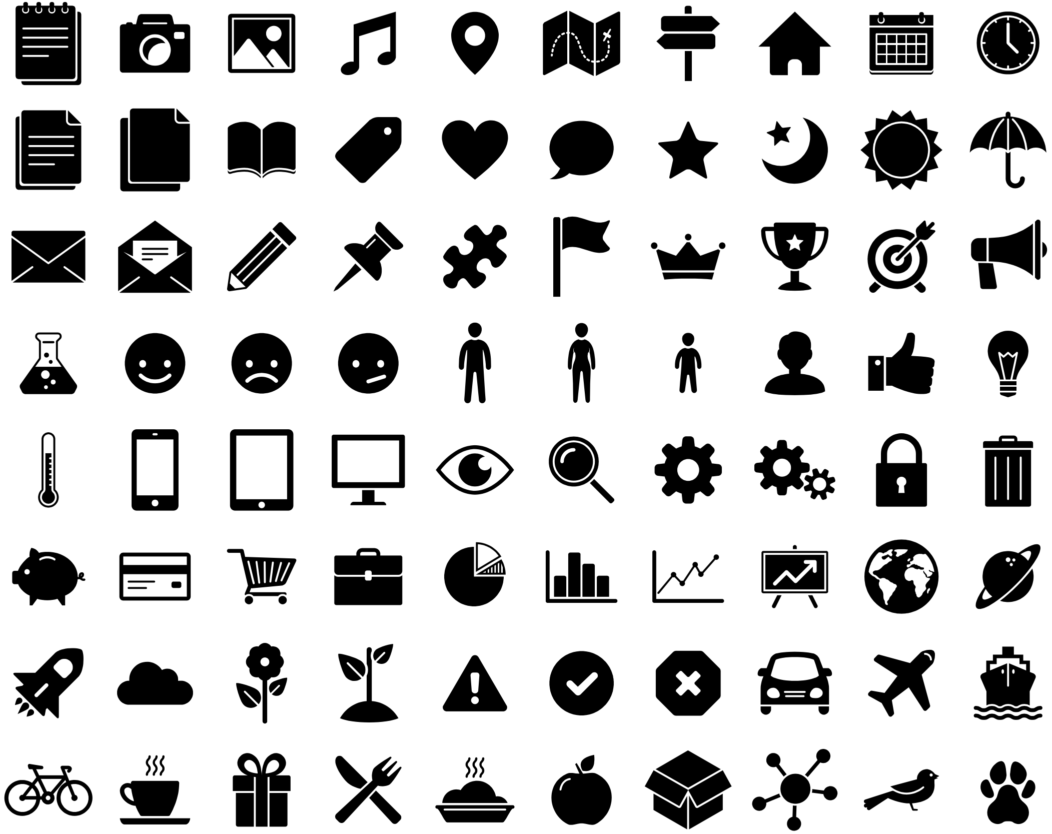
You can find me at

- vinodkk@iitk.ac.in
- http://home.iitk.ac.in/~vinodkk/

Codes Released

https://vinodkkurmi.github.io/DiscriminatorDomainAdaptation/

Scan me



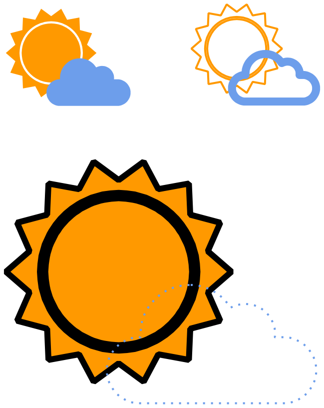
SlidesCarnival icons are editable shapes.

This means that you can:

- Resize them without losing quality.
- Change fill color and opacity.
- Change line color, width and style.

Isn’t that nice? :)

Examples:



Now you can use any emoji as an icon!
And of course it resizes without losing quality and you can change the color.

How? Follow Google instructions
https://twitter.com/googledocs/status/730087240156643328

and many more...