# Unsupervised Domain Adaptation Utilizing CycleGAN

- Dipesh Tamboli

# What is domain-shift and domain-adaptation?

# Datasets with same labels but different distribution

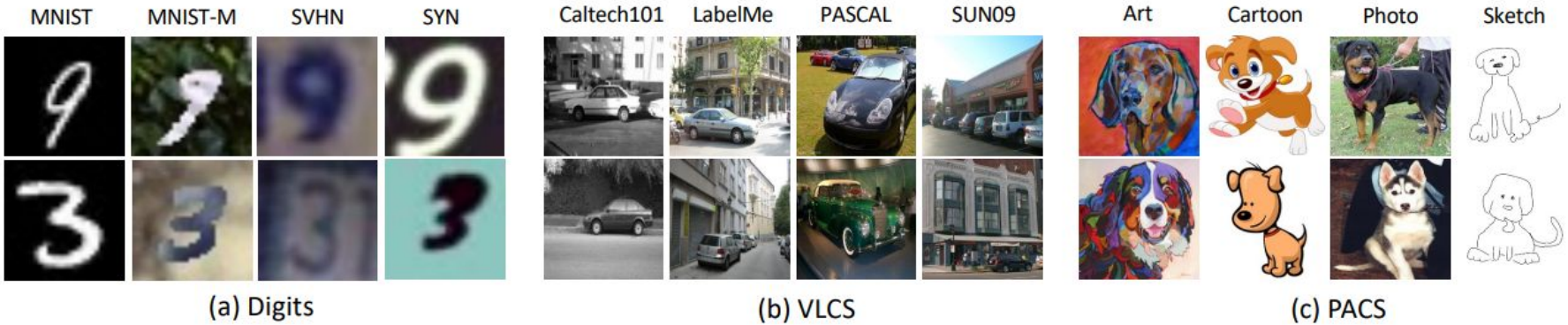
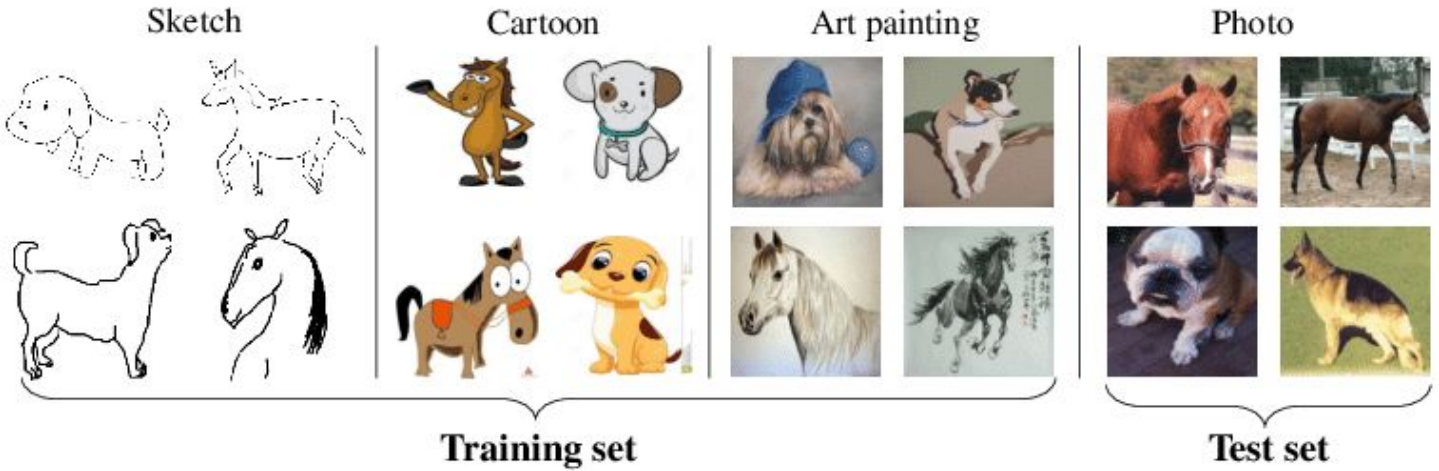



Fig. 1. Example images from three domain generalization benchmarks manifesting different types of domain shift. In (a), the domain shift mainly corresponds to changes in font style, color and background. In (b), dataset-specific biases are clear, which are caused by changes in environment/scene and viewpoint. In (c), image style changes are the main reason for domain shift.

Ref: Zhou, K., Liu, Z., Qiao, Y., Xiang, T., & Loy, C. C. (2021). Domain generalization in vision: A survey. arXiv preprint arXiv:2103.02503.

# Domain Shift




Distribution is different for the training and test set

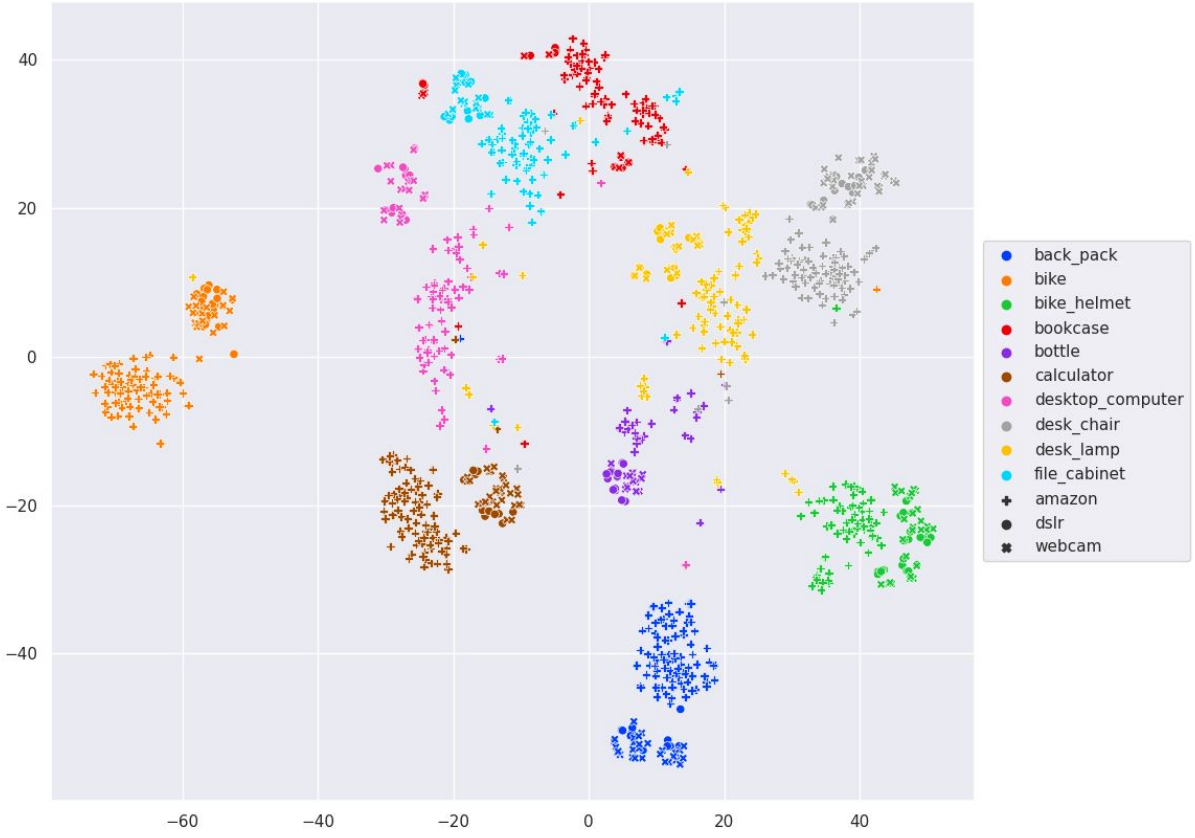
Ref: Generalizing to Unseen Domains: A Survey on Domain Generalization - Scientific Figure on ResearchGate. Available from: https://www.researchgate.net/figure/Examples-from-the-dataset-PACS-1-for-domain-generalization-The-training-set-is_fig1_349787277 [accessed 22 Nov, 2021]

# Motivation - Poor Accuracy on Target domain

- If we train our dataset on a source domain and test on the target domain, the results are not good

| | Accuracy | | | |
|---|---|---|---|---|
| | Train | Test | | |
| **Source Domain** | Source | Amazon | DSLR | Webcam |
| Amazon | 96.13 | **87.94** | 31 | 59.12 |
| DSLR | 90.2 | 46.63 | **85** | 81.97 |
| Webcam | 96.226 | 47.34 | 55 | **98.11** |

# Motivation - Poor feature alignment



# Solution - Domain Adaptation

Different type of Domain Adaptation methods

- Pixel level
  - Changing image input to adapt for the source domain
- Feature level
  - Training the feature extractor to extract domain invariant features

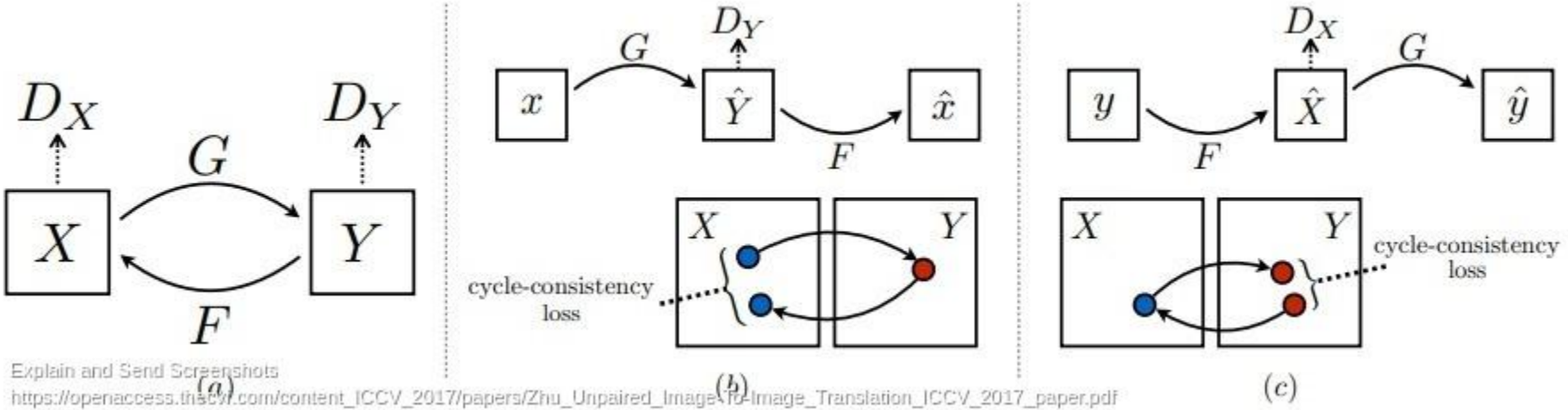
We are focussing on a Pixel-level method in this project.

# CycleGAN

# Unpaired image-to-image translation

Ref: https://github.com/junyanz/pytorch-CycleGAN-and-pix2pix/blob/master/imgs/horse2zebra.gif

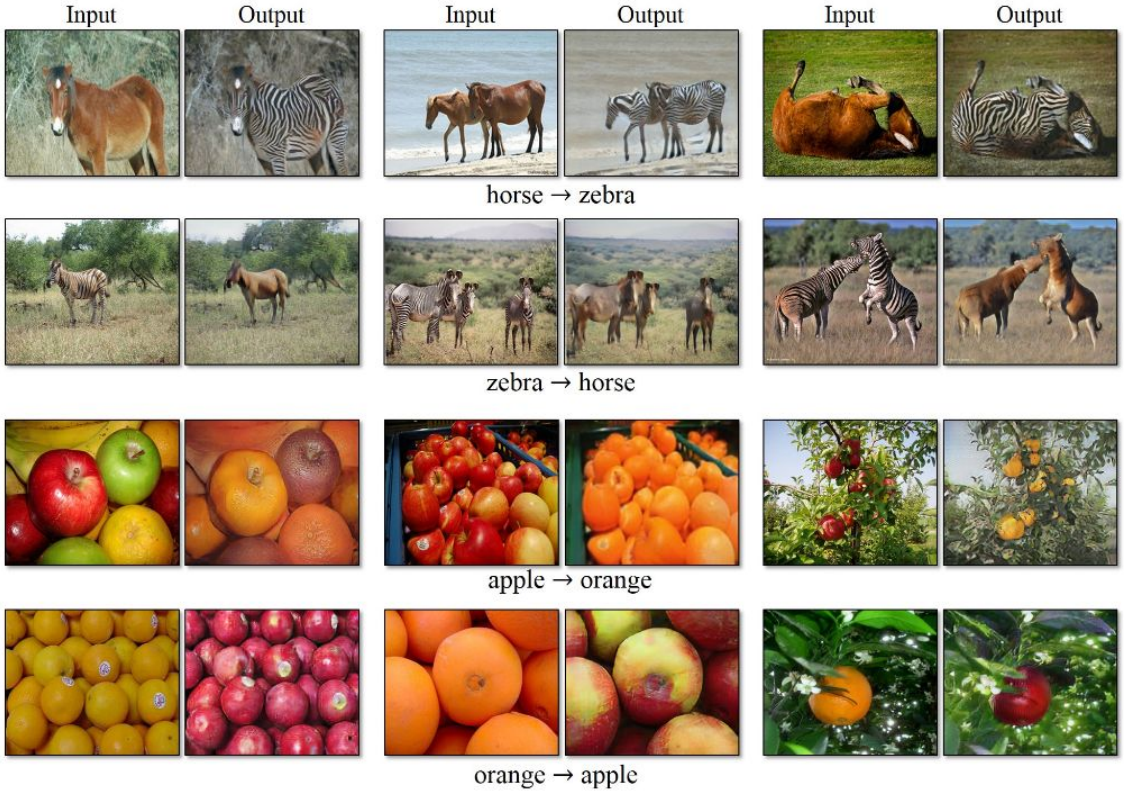
# Cycle consistency and adversarial loss






Ref: Zhu, J.-Y., Park, T., Isola, P., and Efros, A. A. Unpaired image-to-image translation using cycle-consistent adversarial networks. In Proceedings of the IEEE International Conference on Computer Vision (ICCV),Oct 2017.
URL:https://openaccess.thecvf.com/content_ICCV_2017/papers/Zhu_Unpaired_Image-To-Image_Translation_ICCV_2017_paper.pdf.

# Unpaired image-to-image translation




Ref: https://junyanz.github.io/CycleGAN/

# Implementation

- We have reproduced CycleGAN results mentioned in the paper
- Implemented CycleGAN on Office-31 dataset
- Trained Resnet-18 for the classification task on Office-31 dataset
- t-SNE plot for explaining poor accuracy on cross-domain testing
- We have used this **CycleGAN** in an **Unsupervised** manner to convert images from Target to Source domain for testing

# Reproducing CycleGAN results

*Figure 9.* Horse to Zebra style

*Figure 8.* Photo to Van Gogh style

# Office-31 dataset


Ref: CLDA: an adversarial unsupervised domain adaptation method with classifier-level adaptation - Scientific Figure on ResearchGate. Available from: https://www.researchgate.net/figure/Some-examples-on-office-31-dataset_fig4_340846957 [accessed 22 Nov, 2021]

# Implementing CycleGAN on Office-31 dataset - results

. Real DSLR

. Fake Amazon

. Real Amazon

. Fake DSLR

# Implementing CycleGAN on Office-31 dataset

. Real DSLR

. Fake Webcam

. Real Webcam

. Fake Amazon

. Real DSLR

. Fake Webcam

. Real Webcam

. Fake Amazon

# Training Resnet-18 for the classification task on Office-31

| | Accuracy | | | |
|---|---|---|---|---|
| | Train | Test | | |
| **Source Domain** | Source | Amazon | DSLR | Webcam |
| Amazon | 96.13 | **87.94** | 31 | 59.12 |
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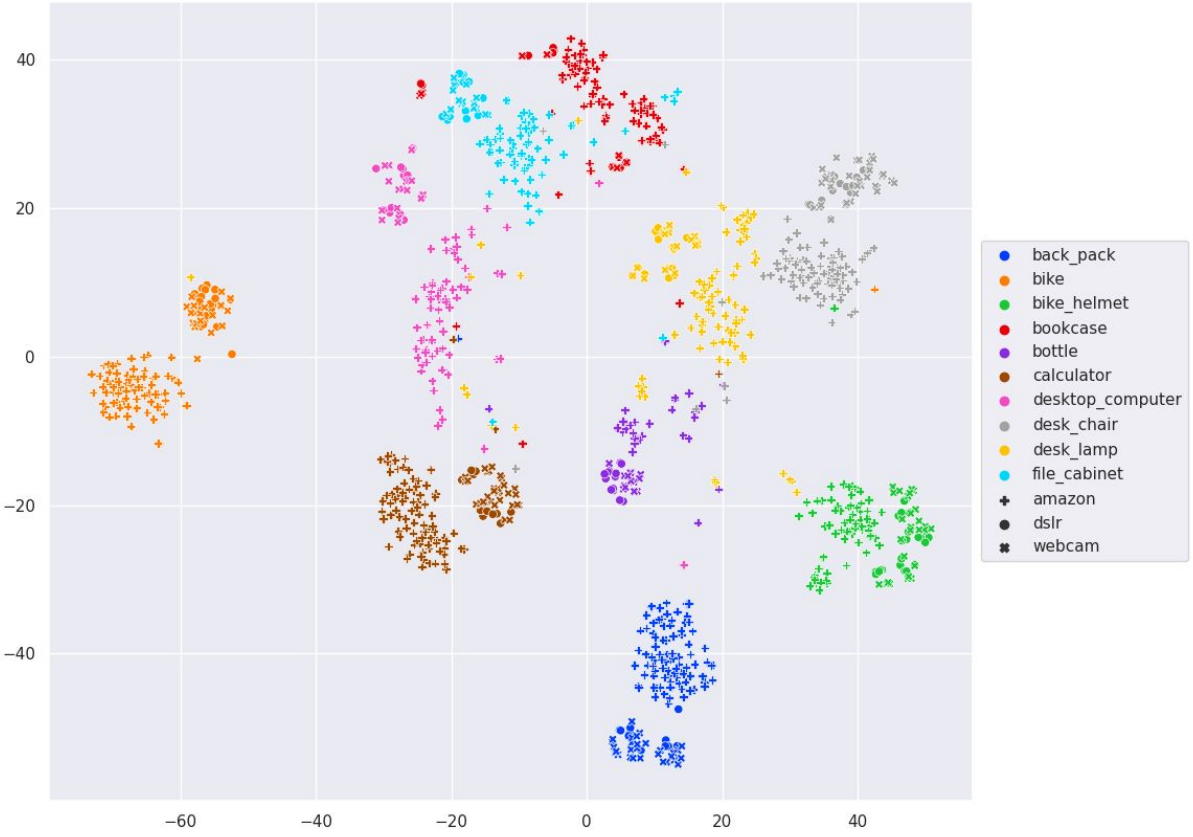
# Training Resnet-18 for the classification task on Office-31



# Convert images from Target to Source

DSLR - prediction: file cabinet . Fake Amazon - prediction: Stapler

# Convert images from Target to Source

. Amazon - prediction: paper notebook

. Fake Webcam - prediction: pen

# Conclusion and take-home message

- CycleGAN translates images from domain-1 to domain-2 in an Unsupervised way
- Generated images using CycleGAN are not that good and natural looking
- It can be useful in the scenarios where labelled data is not available and still we need to use the unlabelled data (Google images, etc.)

# Future Work

- Trying Domain Adaptation with a method which can provide a good resolution generated images
- Adapting at feature level rather on pixel level

# References:


- Zhu, J.-Y., Park, T., Isola, P., and Efros, A. A. Unpaired image-to-image translation using cycle-consistent adversarial networks. In Proceedings of the IEEE International Conference on Computer Vision (ICCV),Oct 2017. URL:https://openaccess.thecvf.com/content_ICCV_2017/papers/Zhu_Unpaired_Image-To-Image_Translation_ICCV_2017_paper.pdf.
- Zhou, K., Liu, Z., Qiao, Y., Xiang, T., & Loy, C. C. (2021). Domain generalization in vision: A survey. arXiv preprint arXiv:2103.02503.
- Generalizing to Unseen Domains: A Survey on Domain Generalization - Scientific Figure on ResearchGate. Available from: https://www.researchgate.net/figure/Examples-from-the-dataset-PACS-1-for-domain-generalization-The-training-set-is_fig1_349787277 [accessed 22 Nov, 2021]